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Essays on Empirical Macroeconomics

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Declaration of Authorship

I, Nikoleta Anesti, declare that this thesis titled, "Essays in Empirical Macroeconomics" and the work presented in it are my own. I confirm that:

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- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.

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To my parents for their endless support.

Chapter 1

Introduction

The collapse of Lehman Brothers, a sprawling global bank, in September 2008 almost brought down the world's financial system. It took huge bail-outs, mainly paid by taxpayers to shore up the industry. Even so, the ensuing credit crunch turned what was already a severe downturn into the worst recession in 80 years. Massive monetary and fiscal stimulus prevented a further depression, but the recovery remains feeble compared with previous post-war upturns. GDP is still below its pre-crisis peak in many rich countries, especially in Europe, where the financial crisis has evolved into the euro crisis. The effects of the crash are still rippling through the world economy, as witnessed in the downturn in financial markets not only in developed but also emerging economies. However, this financial and economic turmoil renewed academic interest in properly understanding the connection between the real economy and the financial sector, but also the use of information from the financial sector as early warning signals for such economic downturns that can be used to gauge the degree of strains in financial markets.

Within this spirit, the second chapter of this Thesis aims to shed light in the empirical investigation of the propagation mechanism of credit shocks within the Euro Area. The main contribution of this paper is to characterise the dynamic effects of these shocks using a structural factor model, Factor Augmented VAR approach, with large panels of Euro Area monthly data that includes financial and economic indicators on an aggregate level. Although the dynamic effects of credit shocks have been extensively studied, there is not much empirical evidence for the Euro Area and especially in data rich environment. Within the suggested context, the identified credit shocks, interpreted as unexpected deteriorations of credit market conditions, immediately increase credit spreads, decrease rates on Euro Area yield curve, and cause large and persistent downturns in the activity of many economic sectors. The impulse responses derived from a structural factor-augmented vector autoregression, show that such shocks are considered to have significant effects on real activity measures, aggregate prices, leading indicators, and credit spreads. The proposed identification strategy imposes a minimum set of restrictions between the financial and macroeconomic indicators and still yields economically meaningful factors. Indeed, shocks emerging from the credit market seem to account for more than 30% of the forecast error variance in economic activity at the six- to sixty-month horizon. Overall, our results imply that credit market shocks have contributed significantly to the Euro Area economic fluctuations especially during the Great Recession.

The famous paper of Bernanke, Boivin and Elliaz [12] (hereafter Bernanke et al.) showed that although structural vector autoregressions (SVARs) are widely used to trace out the effect of monetary policy innovations on the economy, the sparse information sets typically used in these empirical models lead to at least two potential problems with the results. First, to the extent that central banks and the private sector have information not reflected in the VAR, the measurement of policy innovations is likely to be contaminated. A second problem is that impulse responses can be observed only for the included variables, which generally constitute only a small subset of the variables that the researcher and policymaker care about. In their paper, they investigate one potential solution to this limited information problem, which combines the standard structural VAR analysis with recent developments in factor analysis for large data sets. They show empirically that the information that our factor-augmented VAR (FAVAR) methodology exploits is indeed important to properly identify the monetary transmission mechanism and overall the results provide us with descriptive picture of the effect of monetary policy on the economy.

Parallel to this, another transmission channel has been introduced to the literature and has received significant attention from a theoretical and an empirical point of view. Financial frictions are important when we attempt to establish a connection between the credit market conditions to economic activity, as the composition of the borrowers' net worth become crucial due to the incentive problems faced by the lenders Bernanke and Gertler [13] and Bernanke, Gertler and Gilchrist [14]: a borrower with a low net worth relative to the amount borrowed has a higher incentive to default. Given this agency problem, the lender demands a higher premium to provide external funds, which increases the external finance premium. Therefore, economic decline and related drop in asset values tend to generate an increase in the external finance premium for the borrowers that hold these assets in their portfolio. The so-called financial accelerator mechanism rises when the higher external finance premium leads to cuts in Investment and hence in Production, Employment and as a result, in the overall economic activity, which pushes asset prices to fall even more and so on.

In chapter 2, we investigate and establish an empirical link between the financial markets,through the credit market conditions with the real economy and provide a full description of the effects of credit shocks on the economy. The empirical model is estimated using a large number of Euro Area aggregate time series including financial and economic indicators in monthly frequency starting in January 2000 and ending in December 2012. This is a two-step approach where initially, in order to recover the space spanned by structural shocks (including shocks to credit spreads), we estimate factors as principal components from standardised data panels. These common factors are supposed to capture the key aggregate fluctuations in economic and financial series. All economic and financial indicators may be decomposed into a component contemporaneously related to the common factors, and a series-specific (idiosyncratic) component which is unrelated to aggregate conditions. Then, a finite-order VAR approximation of the factors dynamics is estimated. The suggested identification strategy of shocks to credit conditions is achieved by imposing identifying restrictions on the impact matrix of the structural shocks on a few selected observable variables, as proposed by Stock and Watson [100] although within a different context. This allows us to impose the minimum amount of restrictions necessary to identify shocks to credit conditions. This strategy identifies the credit shocks by restricting only the responses on the impact matrix of a few economic indicators and has the important advantage of leaving the dynamics of the factors completely unconstrained, allowing the identified structural shocks to have contemporaneous effects on all factors which drive the panel of indicators. Another attractive feature of the suggested identification strategy is that although we distinguish between financial and other economic factors, we do not require the former to be orthogonal to the latter which can be a rather unrealistic and economically counterintuitive assumption. The empirical results as described by the impulse response analysis suggest that an unexpected widening in the credit spreads result in a gradual decrease in industrial production, which reaches its maximum effect after around two years, before reverting to the baseline scenario. In its turn, capacity utilisation reaches its maximum decline roughly two years after the monetary tightening, after which it eventually returns towards zero. The reaction of consumption expenditure is also in line with expectations, in the sense that a higher short-term interest rate makes financing more expensive, leading to a decrease in private consumption, with the maximum impact (0.2% in the baseline FAVAR) being reached around 20 months after the shock. Also as expected, total employment falls after the disturbance but this movement is also not very persistent, and starts to revert two years after the shock. The behaviour of retail trade and business sentiment indicators is also in line with theory, since a wider credit spreads have a negative impact on these variables, but that eventually fades out. This is also true for the producer price index for industry and the ECB commodity price index. Nevertheless, in spite of the expected shape of the response of the commodity price index, the magnitude of the response is much higher than expected, and therefore has to be interpreted with caution. Moreover, the extra information generated by the

FAVAR approach brings to light some interesting results as regards the responses of the components of the Harmonised Index of Consumer Prices (HICP). In fact, it seems that the intuitive negative response of inflation (total index) is strongly driven by the component energy and unprocessed food, which shows a significant decrease after the shock.

In chapter 3 of the Thesis, we examine the forecasting ability of two different time series models to outperform the naive random walk benchmark in terms of statistical errors and of their ability to generate trading profits in an investment portfolio context. This chapter attempts to shed light into the challenging talk of forecasting exchange rates with models based on economic theory, especially when compared to simple univariate driftless random walk models. Multivariate time series seem to suffer from the same curse. This paper explores the issue of forecasting a large panel of USD exchange rates using two different alternatives, namely, a Factor Model and a Bayesian VAR and compares their predictive performance against the benchmark model, the naïve random walk. As the exchange rates tend to co-move, the use of an extensive set of them may contain valuable information for forecasting. Based on this assumption, this paper contributes to the literature by estimating time-series models that take advantage of this cross-sectional information of the panel of exchange rates and at the same time explore the usefulness of information contained in large data sets. We generate forecasts for all the 24 exchange rates in the panel and show that the Factor Model generates systematically more accurate forecasts than the Bayesian VAR specification although the evidence against the random walk for most of the countries and forecasting horizons, including the 1-step ahead is more mixed. A different dimension of the contribution of this paper is the assessment of the forecastability of the panel of exchange rates based on their ability to generate significant trading profits in investment portfolio context apart from statistical measures.

The literature on the out-of-sample predictability of exchange rates initiates with the study of Meese and Rogoff [87] in 1983 that, in their pioneering work, marked that standard exchange rate models could not outperform the simple random walk forecasting model. They compared the forecastablility of several models specification for three major currencies against U.S. dollar. According to their findings, for the floating-rate period from March 1973 to June 1981, the simple driftless random walk model seems to perform better than all the rest models, regardless of their specification. The authors ascribed the failure of the structural models to the failure of the goods market assumption, money-demand equations and to the difficulties of predicting accurately the expected inflation rate. The very strong negative results of this study spawned an enormous amount of subsequent research that varied econometric techniques or the information set to try to rescue the ability of fundamental models to forecast exchange rates.

A parallel finding in the literature that provided a boost in the developments of econometric methods for the analysis of large datasets is applied in the context of a factor model started with the pioneering work of Stock and Watson [104] [98], where each of a large set of variables is split into a common component, driven by a very limited number of unobservable factors, and an idiosyncratic component. Factor analysis is purely statistical relying on a minimum set of restrictions and assumptions and is a simplifying method to identify patterns that can account for most of the variations in the covariance or correlation matrix of the data. An alternative approach, which also attempts to deal with the "curse" of dimensionality, applies a Bayesian Vector Autoregression (BVAR) approach, in which the VAR coefficients are shrunk towards a random walk representation. The inclusion of prior information in the model contributes to a more efficient summary of the information contained in large datasets, like exchange rates panel, especially when compared to a simple multivariate model that faces the dimensionality problem.

The main message from the empirical results is that, as it was already confirmed by the previous empirical literature, beating the naive random especially for the 1-step ahead forecasting horizon is challenging. However, when compared the two multivariate time series models under examination, i.e the BVAR and the factor model, it seems that the Factor Model produces fairly good forecasts. More precisely, for these currencies that the factor model outperforms the random walk, where the U-Theil statistics is below 1, the average gains for all the forecast horizons range from 1 to 3%. The pattern of the gains, in the majority of the cases, has a U-shape, namely there are gains around 1% at very short and very long forecast horizons, and larger gains at intermediate forecast horizons.

A more disaggregate investigation shows that for the 1-step ahead forecasting horizon the factor model outperforms the random walk in only 3 cases out of 24, however for h=3 and h=6 the factor model is better in 12 cases out of 24, and in 14 cases for $h = 12$. For the Euro-Dollar and the GBP-Dollar exchange rates, the factor model outperforms the random walk at all horizons, generating a value for the U-Theil statistics lower than 1. For example, for h=12, the gain in forecasting accuracy in the Euro-Dollar exchange rate is 2.2%, 3.6% for the GBP-Dollar exchange rate respectively. For the Yen-Dollar rate the evidence is more mixed, as the naive random walk seems to outperform, with the BVAR providing better forecasts at longer horizons, with smaller gains when compared to the factor model specification. For two major trading partners of the US, Canada and Mexico, the BVAR performs very well for the former country, with gains ranging from 1% for $h = 1$ to 9% for $h = 12$, and only slightly worse for the latter country at short horizons, with losses smaller than 4% and gains of about 2.5% for $h = 5$. However, the Giacomini and White [59] statistic denotes rejection of the null of equal forecast accuracy of the models at 1%, 5%, and 10% indicates that although the RMSFE across currencies is below 1 in several instances, only in a few cases the differences in the forecasts are statistically significant different from zero.

Finally, an interesting pattern arises from the forecasting results of the Factor Model, if we split the results into 'developed' and 'emerging' currencies, while the developed economies do systematically better against the random walk specification and the statistical gains are larger on average, the evidence is more mixed when it comes to the emerging economies (although Factor Model remains a better forecasting model compared to the BVAR and AR with optimal number of lags (L*) specifications). Especially for some currencies, like the Indonesian Rupiah and the Russian Ruble, the results were not that encouraging. A potential explanation of this finding might be approached if the nature of the cross sectional information picked up by the model is explored in details by assessing the cross sectional dependence among the different groups of currencies.

The forecasting results based on the multivariate time series models using statistical measures are interesting. However, they indicate little about the ability of the statistical approach to generate persistent economic profits in an investment portfolio context. It becomes obvious from the results that overall the strategy based on the dynamic factor model specification provides on average positive returns. Moreover, the factor model strategy performs better than the one based on the AR in terms of both returns and standard deviation, as shown by the Sharpe Ratios, which are higher in 14 cases out of 24 and when comparing the Factor Model specification with the BVAR in terms of Sharpe ratios, then the Factor Model specification generates higher ratios in 16 out of 24 cases under consideration. Finally, it is worth noting that this strategy involved systematically fewer transactions with respect to the BVAR and AR, i.e. this model induces the investor to change his position less often, which means that the transaction costs associated with such strategy would be smaller.

Overall, the empirical results suggest that although beating the naive random walk is a challenging task, time series multivariate modelling appears to summarise the cross sectional information of exchange rates rather well. The factor model approach through the Principal Components analysis provides us with rather accurate forecasts of the future path of the exchange rates by extracting all the information available in the cross section panel of exchange rates. Finally, the forecasts derived by the models under examination are being evaluated on their ability to generate profitable trading strategies and in the majority of the cases the strategies based on the factor model perform better in terms of average returns and Sharpe Ratios.

In chapter 4 of the thesis, the task of constructing an index for the Euro Area GDP growth is being considered, as part of a nowcasting exercise using a pseudo-real time dataset, i.e forecasting the GDP growth of the current quarter, as new information becomes available. Due to the recent economic turmoil affecting the world economy, there has been an explosive literature that focuses on the early and accurate assessment of the short term evolution of economic activity that is of particular interest not only for academics, but also practitioners. The academic literature and the press are full of references to short term GDP growth rate forecasts and its successive revisions which are currently deteriorating with ongoing economic developments. However, the vast majority of the forecasts released by relevant institutions do not always make explicit the methodology followed to compute their forecasts. To predict GDP, the existing models usually rely on quarterly series which are published with a delay which ranges from about 45 to 60 days. Therefore, these forecasts, apart from not capturing the abrupt economic changes occurring in the meantime, they will also be subject to strong revisions in the reference series. With this outdated information the standard autoregressive models usually exhibit strong mean reverting behaviour and their forecasts are therefore seriously biased towards the mean which may lead to misleading forecasts in an environment of economic turbulence. Within this spirit, the purpose of this paper is to construct and estimate a small scale factor model to compute short term forecasts of the Euro Area GDP growth rate using a pseudo real-time dataset. The model aims at dealing with the typical problems rising from the different releases of the economic indicators. First, the model deals with ragged edges in order to take into account all the available information which is released in a non-synchronous way. Second, the model accounts for data with mixed frequencies, in order to bridge monthly indicators with quarterly GDP. Third, the model is a simple algorithm that can be automatically updated, so the model handles potential economic instabilities, because, if the predictive power of any variable diminishes during the course of some periods, the variable will reduce its weight and its loading factor. Finally, the model is dynamically complete in the sense that it accounts for the dynamics of all the indicators used in the analysis. This leads the model to be a metric to measure the news associated with each realisation of the indicators used in the analysis, based on the effect that each realisation has on the expected quarterly economic growth.

The maximum likelihood estimates of the factor loadings indicate that apart from the GDP, the economic indicators with larger loading factors are those corresponding to Industrial Production Index, Total Retail Sales Volume, Industrial New Orders, and Extra-Euro Exports. The indicators with lower correlation with the latent common factor are the Euro Area Economic Sentiment indicator and the Consumer Confidence indicator which are only marginally significant. However, the estimates are always positive and statistically significant, indicating that these series are procyclical, i.e., positively correlated with the common factor. In addition to GDP forecasts, the model computes accurate forecasts for the whole set of indicators since their specifications are dynamically complete inside the model. The accuracy of these forecasts is crucial for forecasting exercises about the expected changes in GDP predictions against different possible subsequent values of these indicators. Overall, this index although at a rather preliminary stage, provides us with a statistical framework that exploits information from the business cycle dynamics within the Euro Area and gives us a solid basis for further extensions and improvements.

Chapter 2

A FAVAR Approach to Credit Shocks in the Euro Area

2.1 Introduction

After markets for securitised credit products collapsed dramatically in the second half of 2007, growth in a number of industrialised economies slowed significantly, suggesting that disruptions in financial markets can generate important macroeconomic consequences. Sharp and sudden deteriorations in financial conditions are typically followed by a prolonged period of economic downturns in the U.S. and other economies as well. During periods of credit market turmoil, financial asset prices, because of their forward-looking nature, can be particularly informative connections between the real and the financial side of an economy: Volatility in asset prices can not only be an early-warning signal for such economic downturns but also used to measure the degree of strains in financial markets. Different studies, among others, Stock and Watson [94] [104] and recently Mueller [89] have analysed the predictive ability of various corporate credit spreads to forecast economic growth using dynamic factor analysis.

Additionally, while corporate bond yields incorporate information about future economic conditions, Gilchrist, Yankov and Zakrajsek [63] and also Gilchrist and Zakrajsek [64] re-examined this evidence using a broad array of credit spreads constructed directly from the secondary bond prices on outstanding senior unsecured debt issued by a large panel of nonfinancial firms. Indeed, shocks emanating from the corporate bond market are able to generate large and persistent contractions in economic activity and other macroeconomic variables. It also appears that credit market shocks have contributed significantly to the U.S economic fluctuations during the 1990-2008 period. Credit risk is characterised by three types of risk, namely, default risk; downgrade risk; and credit spread risk. Default risk is the risk that the issuer will be unable to honour his contractual obligations in full and on time. Downgrade risk is the risk that a recognised rating agency will reduce the credit rating of an issuer. This deterioration of credit-worthiness reflects the issuer's capacity to honour his debt obligation and affects the price of the security issued by the issuer. Credit spread risk is the risk that the yield premium or the spread over a reference rate will increase for a debt obligation due to adverse changes in market conditions. These risks do not appear, at first, to be interrelated; however, default is the product of a series of downgrades and credit spread widening which reflects the gradual inability of the issuer to honour his debt obligations.

As a consequence, the strong tightening in the credit conditions in 2007 and 2008 followed by the associated contraction in economic activity suggests that credit conditions may have important effects on the economy. Understanding and evaluating the joint dynamics of the real economy and the financial sector could lead to more preemptive policy responses. A more comprehensive analysis of the quantitative effects of credit shocks focusing mainly on Euro Area variables is required in order to capture the joint dynamics within a sufficient rich empirical framework.

In this paper, we re-examine the empirical evidence of the propagation mechanism of credit shocks on economic activity and other macroeconomic variables. We seek to characterise the dynamic effects of credit shocks using a structural factor model, Factor Augmented VAR (FAVAR) model with large panels of Euro Area monthly data that includes financial and economic indicators at an aggregate level.

Contrary to the standard structural VAR models, factor models have a number of advantages and appear to have addressed successfully various empirical puzzles.

Firstly, they permit considering the large amount of information potentially observed by agents, and so minimise the risk of omitted variable bias, they are not sensitive to the choice of a specific data series, which may be arbitrary, to represent a general economic concept, they are less likely to be subject to non-fundamentalness issues raised by Forni, Giannone, Lippi and Reichlin [55] and finally they allow us to compute the response of a large set of variables of interest to identified shocks in order to fully describe the effects of the structural shocks to the variables under consideration.

The empirical model is estimated using a large number of Euro Area aggregate time series including financial and economic indicators along the lines of Bernanke et al. [12] that estimated the effects of a monetary policy shock within a FAVAR framework. This is a two-step approach where first, in order to recover the space spanned by structural shocks (including shocks to credit spreads), we estimate factors as principal components from standardised data panels. These common factors are supposed to capture the key aggregate fluctuations in economic and financial series. All economic and financial indicators may be decomposed into a component contemporaneously related to the common factors, and a series-specific (idiosyncratic) component which is unrelated to aggregate conditions. Then, a finite-order VAR approximation of the factors dynamics is estimated. The identification of shocks to credit conditions is achieved by imposing identifying restrictions on the impact matrix of the structural shocks on a few selected observable variables, as proposed by Stock and Watson [100]. This allows us to impose the minimum amount of restrictions necessary to identify shocks to credit conditions, as first proposed by Boivin, Giannoni and Stevanovic [17] for the US market.

The empirical framework and the identification strategy is related to that of Gilchrist, Yankov and Zakrajsek [63], but differs from it in significant ways. In order to determine their credit shocks, the authors impose potentially strong identifying assumptions. More specifically, they impose that no macroeconomic variable, including all measures of economic activity, prices or interest rates can respond contemporaneously to credit shocks. This assumption may be restrictive, if for example, changes in credit spreads affect contemporaneously overall financial conditions, including interest rates. It may potentially attribute an overall strong effect of credit spreads on economic variables by preventing a possible contemporaneous drop in the yield on riskless securities, which might mitigate the effect of a credit tightening. Furthermore, they assume that the factors summarising macroeconomic indicators are contemporaneously uncorrelated with the factors summarising all credit spreads, regardless of the source of disturbances.

Our results show that an unexpected increase in credit spreads causes a significant contemporaneous drop in the Euro Area yield curve at various maturities, and has a significant effect in the same month on other variables such as consumer expectations, commodity prices, capacity utilisation, hours worked, housing starts, etc, a result that contrasts the assumption made by Gilchrist, Yankov and Zakrajsek [63]. This unexpected increase in the external finance premium also results in a significant and persistent economic slowdown, in the months following the shock. The responses generated by our identifying procedure yield a realistic picture of the effect of credit shocks on the economy, and provide valuable information about the transmission mechanism of these shocks. In addition, we find that the extracted common factors capture an important dimension of the business cycle movements. Furthermore, we find that credit shocks have quantitatively important effects on several indicators of real activity and prices, leading indicators, and credit spreads, as they explain a substantial fraction of the variability of these series. Results from a counterfactual experiment indicate that the credit shocks explain a large part of the decline in many activity and price series, as well as the monetary policy interest rate (EONIA) in 2008 and 2009. Finally, a further advantage of the identification procedure is that it allows us to recover underlying structural factors that have an interesting economic interpretation. Those factors can be obtained by judiciously combining the initially extracted factors. Our empirical analysis considers a battery of specifications. These findings are robust to different identification schemes. The first FAVAR model that we consider is estimated using a monthly balanced panel. We impose a recursive assumption to identify structural shocks. The responses of key macroeconomic series to credit shocks are found to be qualitatively similar to those from a small-scale VAR model. However, credit shocks are found to generate a substantially larger share of economic fluctuations in the FAVAR model than in the small-scale VAR. Given that the VAR likely omits relevant information, this suggests that the VAR may be misspecified and does not properly capture the source or propagation of key structural shocks. In addition, the factor model gives a more complete and comprehensive picture of the effects of credit shocks since the impulse responses and the variance decomposition of all variables can be obtained. As mentioned above, our approach produces interpretable common factors. Indeed, the first structural factor is highly correlated with price measures, the second factor is important for the unemployment rate, while the third is related to interest rates, and the fourth factor is correlated with credit spreads. Overall, the results are quite robust: in each specification, an adverse shock to credit conditions causes a significant and persistent economic downturn. This reinforce our empirical evidence about the real effects of financial disturbances on economic activity.

In Section 2.2 we briefly review some mechanisms drawing from theoretical models that link credit shocks and economic variables. Section 2.3 presents the structural factor model and discusses various estimation and identification issues. Section 2.4 presents the dataset and the model specifications. The main results are presented in Section 2.5, followed by the robustness analysis and Section 2.6 concludes.

2.2 Theoretical Background

In this section, we briefly summarise some of the mechanisms that connect the financial and economic variables and the channels which shocks to the credit market propagate in the economic activity.

Financial frictions are significant when we attempt to establish a connection from the credit market conditions to economic activity, as the composition of the borrowers' net worth become crucial due to the incentive problems faced by the lenders. Bernanke and Gertler [13] and Bernanke, Gertler and Gilchrist [14] established how a borrower with a low net worth relative to the amount borrowed has a higher incentive to default. Given this agency problem, the lender demands a higher premium to provide external funds, which increases the external finance premium. Therefore, economic decline and the related drop in asset values tend to generate an increase in the external finance premium for the borrowers that hold these assets in their portfolio. The so-called financial accelerator mechanism rises when the higher external finance premium leads to cuts in Investment and hence in Production, Employment and as a result, in the overall economic activity, which pushes asset prices to fall even more and so on.

Several other transmission channels, focusing on the credit supply, have also been introduced in the literature. The narrow credit channel or traditional "bank lending" channel focuses on the financial frictions deriving from the balance-sheet situation of banks. It assumes that a monetary policy tightening raises the opportunity cost of holding deposits, which in turn leads banks to reduce lending on account of the relative fall in funding sources. In other words, it contends that after a monetary policy tightening, banks are forced to reduce their loan portfolio due to a decline in total reservable bank deposits.

The broad credit channel also includes the "balance-sheet" channel, in which the financial circumstances of borrowers (households and firms) can augment real economy fluctuations (see Bernanke and Gertler [13]). Ang et al. [2] also provide evidence for the existence of a broad credit channel in many of the largest euro area countries over the period 1993-1999. The results from this collection of studies suggested that the key factor in Europe seemed to be whether banks were holding high or low levels of liquid assets. Banks holding more liquid assets showed weaker loan adjustment in the wake of changes to the short-term interest rates. But in contrast to the US, monetary policy does not have a greater impact on the lending of small banks. This finding was explained by certain structural characteristics of European banking markets: the importance of banks' networks, state guarantees and public ownership (see Ehrmann [41], Ehrmann and Worms [42]).

More recently, credit risks and their effect on economic activities have been modelled in a general equilibrium framework. Christiano, Motto and Rostagno [28] [27] in a number of papers augmented a medium-size DSGE model similar to Christiano, Eichenbaum and Evans [29] and Smets and Wouters [93] with a financial accelerator mechanism linking conditions on the credit market to the real economy through the external finance premium following Bernanke, Gertler and Gilchrist [14].

They furthermore introduce a so-called "risk shock", which captures the exogenously time-varying cross-sectional standard deviation of idiosyncratic productivity shocks, and which directly moves credit spreads by changing agency costs. Christiano, Motto and Rostagno [28] find that such "risk shock" accounts for a large share of US GDP fluctuations. In addition, Gilchrist, Ortiz and Zakrajsek [62] estimate a similar model in which they introduce two financial shocks: a financial disturbance shock that directly affects the external finance premium (corresponding to the above mentioned "risk shock"), and a net worth shock affecting the balance sheet of a firm. The second shock can be viewed as a credit demand shock, whose effect depends on the degree of financial market frictions. After estimating the structural model using US data covering the 1973-2008 period, Gilchrist, Ortiz and Zakrajsek [62] find that both financial shocks cause an increase in the external finance premium, which, through the financial accelerator, implies a persistent slowdown in economic activity and in investment.

2.3 Econometric Framework and Estimation

Let X_t denote an $N \times 1$ vector of economic time series, Y_t a vector of $M \times 1$ observable macroeconomic variables that constitutes a subset of X_t and F_t a $k \times 1$ vector of unobservable factors that capture most of the information contained in X_t. We might think of the unobserved factors as diffuse concepts such as "economic activity" or "credit conditions" that cannot easily be represented by one or two series but rather are reflected in a wide range of economic variables. Following the standard approach, we might proceed by estimating a VAR, a structural VAR (SVAR), or other multivariate time series model using data for the Y_t alone. However, in many applications, additional economic information, not fully captured by the Y_t, may be relevant to modelling the dynamics of these series.

According to Bernanke et al. [12], the joint dynamics of (F_t, Y_t) can be given by the following transition equation:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \tag{2.1}$$

where $\Phi(L)$ is a conformable lag polynomial of finite order d which may contain a priori restrictions as in the usual structural VAR literature. The error term v_t is mean zero with a covariance matrix Q. Equation 2.1 is a VAR in (F_t, Y_t) and the system reduces to a standard VAR in Y_t if the terms of $\Phi(L)$ that relates Y_t to F_{t-1} are all zero; It may contain a priori restrictions as in the VAR literature, but which includes both observable and unobserved variables. Bernanke et al. [12] refer to Equation 2.1 as a factor-augmented vector autoregression, or FAVAR. There is thus a direct mapping into the existing VAR results, and provides a way of assessing the marginal contribution of the additional information contained in F_t . Besides, if the true system is a FAVAR, note that estimation of 2.1 as a standard VAR system in Y_t that is, without the factors taken into consideration will in general lead to biased estimates of the VAR coefficients and related quantities of interest, such as impulse response coefficients.

Since the factors are unobserved, Equation 2.1 cannot be estimated directly. However, we can interpret the factors, in addition to the observed variables, as the common forces driving the dynamics of the economy. For concreteness, we can assume that the relation between the informational time series X_t, the observed variables Y_t and the factors F_t can be summarised in the following (static) representation of a dynamic factor model:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t \tag{2.2}$$

where Λ^f is a $N \times K$ matrix of factor loadings, Λ^y is $N \times M$ and e_t is the vector of $N \times 1$ error terms weakly cross-sectionally and serially correlated and with mean zero. The specification of the dynamic factor model à la Stock and Watson [96] implies that X_t does not depend on the lagged values of F_t, only on the current ones (static representation of the dynamic factor model). Since we assume that $M + K \ll N$, the amount of information that can be handled in a FAVAR increases significantly in comparison to standard VAR models.

The unknown coefficients in Equation 2.1 could in principle be estimated by Gaussian maximum likelihood using the Kalman filter (or by Quasi Maximum Likelihood), as shown in Engle and Watson [47] and Stock and Watson [94]. This method is however computationally burdensome and is likely to lead to misspecification when N becomes very large. In this framework, we adopt instead an alternative estimation approach based on a two-step principal components procedure, where factors are approximated in the first step, and the dynamic process of factors is estimated in the second step. We rely on the result that factors can be obtained by a Principal Components Analysis (PCA) estimator. Stock and Watson [104] prove the consistency of such an estimator in the approximate factor model when both cross-section and time sizes, N, and T, go to infinity, and without restrictions on N/T. Moreover, they justify using F_t as regressor without adjustment. Bai and Ng [7] furthermore show that PCA estimators are $\sqrt{T}$ consistent and asymptotically normal if $\sqrt{T}/N \to 0$. Inference should take into account the effect of generated regressors, except when T/N goes to zero. The principal components approach is easy to implement and does not require very strong distributional assumptions. Simulation exercises have shown that likelihood-based and two-step procedures perform quite similarly in approximating the space spanned by latent factors. However, since the unobserved factors are first estimated and then included as regressors in the VAR equation, and given that the number of series in our application is small, relative to the number of time periods, the two-step approach suffers from a generated regressors' problem. To get an accurate statistical inference on the impulse response functions that accounts for uncertainty associated to factors estimation, we use the bootstrap procedure as in Bernanke et al. [12].

2.3.1 Time domain analysis of the dynamic factor model

Factor models represent the vector of N time series as a linear combination of two unobserved components,a common component, driven by a small number of factors, plus an idiosyncratic component. Let X_t be the $N \times 1$ vector of stationary zero mean variables under consideration, observed for time $t = 1, 2, \ldots, T$. In the general set-up of a dynamic[1] factor model, each element of the vector $X_{it} = [X_{1t}, \ldots, X_{Nt}]'$ for $i = 1, 2, \ldots, N$, can be represented as:

$$X_{it} = \lambda_i f_t + e_{it} \tag{2.3}$$

where f_t is the $q \times 1$ vector of common factors ($q \ll N$), whose dynamic effects on X_{it} are grouped in $\lambda_i(L) = \lambda_{i0} + \lambda_{i1} L + \lambda_{i2} L^2 + \cdots + \lambda_{ip} L^p$, lag polynomials in nonnegative integer powers of L (where each λ_i is a $N \times q$ matrix) , and $e_t = [e_{1t}, \ldots, e_{Nt}]\prime$ is the $N \times 1$ vector of idiosyncratic disturbances. An alternative formulation of the model is:

$$X_t = \Lambda F_t + e_t \tag{2.4}$$

where $F_t = [f'_t, f'_{t-1}, \ldots, f'_{t-p}]\prime$ is $r \times 1$ so that now $r = (p + 1) \times q$ factors that drive the variables, but the factors have **only** a contemporaneous effect on X_t with loadings grouped in the $N \times r$ matrix $\Lambda = [\lambda_0, \lambda_1, \ldots, \lambda_p]$, the $i-$th row of Λ being $\Lambda_i = [\lambda_{i0}, \ldots, \lambda_{ip}]$. Since the association between factors and variables is only contemporaneous, the dynamic factor model is in its static formulation.

Note that we cannot estimate F_t, but instead we can estimate the common factor space, i.e. a $r-$dimensional orthogonal vector whose entries span the same linear space as the entries of F_t. In fact, the factors are not identified because for any invertible $r \times r$ matrix G, equation 2.4 can be rewritten as

$$X_t = \Lambda G G^{-1} F_t + e_t = \Psi P_t + e_t \tag{2.5}$$

[1] In order to make this terminology clear, it is required to note that the term static in a dynamic factor model refers to the static relationship between the common component and the variable; however, the common component itself can be a dynamic process, i.e. can capture arbitrary lags of some fundamental factors. As Forni [55] assert, when all variables are hit by the common shocks at the same time, the model is called static, whereas when different variables are hit by different lags of the common shocks, the model is called dynamic.

where P_t is an alternative set of factors. In spite of the identification problem (which makes the structural interpretation of the factors more complicated), P_t is simply a linear transformation of F_t, and therefore both are equivalent in summarising the information contained in X_t. In the standard or exact formulation of the factor model, the idiosyncratic components are assumed to be serially and cross-sectionally independent and the factors are assumed to be serially uncorrelated. Moreover, $E[F_t e_t'] = 0$, i.e. the factors and the idiosyncratic components are required to be mutually orthogonal. However, the assumptions of the exact model may be viewed as too restrictive and even unrealistic in economic terms. Stock and Watson [96] developed a nonparametric approach for the time domain analysis of the dynamic factor model based on the static principal components of X_t. The authors show, under the finite lag assumption and some additional technical assumptions, that the common space spanned by the dynamic factors F_t can be estimated consistently by the principal components of the $T \times T$ covariance matrix of X_t, even if some of the restrictive assumptions of the classical model are neglected. In this way, consistency of the estimators requires the factors F_t to be orthogonal, i.e. uncorrelated with the idiosyncratic component. In the approximate factor model limited dependence of the idiosyncratic disturbances is allowed in both dimensions.

The starting point in the approach of Stock and Watson [96] is the estimation of the factors F_t and the loadings Λ. Let the estimators $\hat{F}_t$ be the minimisers of the least squares criterion:

$$V_{N,T}(F, L) = (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \Lambda_i F_t)^2 \tag{2.6}$$

where $F = [F_1, \ldots, F_t, \ldots, F_T]\prime$ and Λ_i is the $i-$th row of Λ, subject to the constraint $T^{-1} F' F = T^{-1} \sum_{t=1}^{T} F_t F_t' = I_q$. Under the hypothesis of k common factors, Stock and Watson [96] show that the least squares estimators of the factors $\hat{F} = [\hat{F}_1, \ldots, \hat{F}_t, \ldots, \hat{F}_T]\prime$ are the k eigenvectors corresponding to the k largest eigenvalues of the $T \times T$ matrix $(N)^{-1} \sum_{i=1}^{N} X_i^* X_i^{*\prime}$, where $X_i^* = [X_{i1}, \ldots, X_{iT}]'$. The least square estimators of the loadings are then obtained from a linear regression (OLS) of the variables on the estimated factors. Moreover, the least squares estimators of the loadings are the k eigenvectors corresponding to the the k largest eigenvalues of the $N \times N$ matrix $(T)^{-1} \sum_{t=1}^{T} X_t X_t'$. The authors prove that when the assumed number of factors, k, is equal to the true number, r, the entries of $\hat{F}_t$ span the same linear space as the entries of F_t. When $k > r$, there are $k - r$ estimated factors are redundant linear combinations of the elements of F_t. When $k < r$, consistent estimation of a subspace of dimension k is preserved, because of the orthogonality hypothesis. Finally, the estimator of the idiosyncratic component is $\hat{e}_t = X_t - \hat{x}_t$.

In order to determine the number of factors needed to properly capture the effects of credit markets disruptions, we follow Bernanke et al. [12] in using the Bai and Ng [8] $IC_2(k)$ criterion, the one that is commonly used for the determination of the number of factors:

$$IC_2(k) = ln(V_{N,T}(\hat{F}_{(k)}, \hat{\Lambda}_{(k)})) + k(\frac{N+T}{NT})ln(min\{N,T\})) \tag{2.7}$$

where $V_{N,T}(\hat{F}_{(k)}, \hat{\Lambda}_{(k)}))$ denotes the sum of squared residuals from a $k-$ factor model, as defined in Equation 2.6 with $\hat{F}_{(k)}$ and $\hat{\Lambda}_{(k)}$ being the estimated factors and loadings. The information criterion reflects the trade-off between goodness-of-fit, on the one hand and overfitting, on the other. The first term on right-hand side of Equation 2.7 shows the goodness-of-fit, as if the number of factors increases, the variance of the factors also increases and the sum of squared residuals decreases. Hence, the information criterion has to be minimised in order to determine the number of factors. The penalty of overfitting, which is the second term on the right-hand side of Equation 2.7 is an increasing function of N and T.

2.3.2 Identification of structural shocks

2.3.3 Exact Identification/Cholesky Factorisation

One of the main objectives of this paper is to identify the effect of shocks to credit conditions on the economy by imposing a minimum set of identifying restrictions. To identify the structural shocks, we employ the contemporaneous timing restrictions procedure as first proposed in Stock and Watson [100]. This procedure identifies credit shocks by restricting only the responses on the impact matrix of a few economic indicators. This approach has the important advantage of leaving the dynamics of the factors completely unconstrained, and allows the identified structural shocks to have contemporaneous effects on all factors which drive the panel of indicators. The approach adopted here contrasts with the one of Gilchrist, Yankov and Zakrajsek [63], in the following aspect: they assume that credit shocks do not have a contemporaneous effect on any of the economic factors and indicators, including interest rates and in addition they estimate two orthogonal sets of factors to those explaining a panel of economic activity indicators, and factors related to credit spreads. We do not need to make such a distinction, and thus do not need to assume that financial factors are orthogonal to other economic factors, which can be a rather unrealistic assumption. Finally, contrary to other identification strategies that have been adopted in analyses using FAVAR models, we do not need to impose that any factor to be an observed factor, nor do we rely on the interpretation of a particular latent factor to characterise the responses of economic indicators to structural shocks.

More precisely, timing restrictions are basically exclusion restrictions implying that specific structural shocks do not affect certain X variables contemporaneously, for example the monetary policy shock does not affect output within the same month. This is a standard approach in the structural VAR literature and within this framework it implies that the innovations in some of the X's depend only on some of the ζ's. The main advantage of this approach is that the dynamics of the factors remain unconstrained so that the identified structural shocks are allowed to have contemporaneous effects on all factors that drive the panel of indicators. The difference in the identification scheme of Gilchrist, Yankov and Zakrajsek [63] is that credit shocks in their framework do not affect contemporaneously any of the economic factors and indicators including the interest rates. Moreover, they also estimated two orthogonal set of factors, those explained by a panel of economic activity indicators and those related to credit spreads. As a result, in their framework the credit shock is identified as innovation to the first "financial factor" obtained as a principal component to a large panel of credit spread data from the US bond market. To identify the credit shocks we start by inverting the VAR process of factors assuming stationarity and substituting the expression to obtain the moving average representation of X_t:

$$X_t = B(L)e_t + u_t \tag{2.8}$$

where $B(L) \equiv \Lambda[I - \Phi(L)L]^{-1}$. The assumption here is that the number of static factors,K is equal to the number of structural shocks and that the factor innovations e_t are linear combinations of the structural shocks ϵ_t:

$$\epsilon_t = He_t \tag{2.9}$$

where H is a nonsingular square matrix and $E[\epsilon_t \epsilon_t'] = I$. Using Equation 2.8 to replace e_t in Equation 2.9 gives the structural moving-average representation of X_t:

$$X_t = B^*(L)\epsilon_t + u_t \tag{2.10}$$

where $B^*(L) \equiv B(L)H^{-1} = \Lambda[I - \Phi(L)L]^{-1}H^{-1}$. In order to be able to identify the structural shocks ϵ_t, we arrange data in X_t and impose contemporaneous timing restrictions on the impact matrix. More precisely, we assume that certain structural shocks do not affect the first few indicators in X_t within the period, so that the impact matrix B_0^* takes the following form:

$$B_0^* = \begin{bmatrix} x & 0 & \cdots & 0 \\ x & x & \ddots & 0 \\ x & x & \ddots & 0 \\ x & x & \cdots & x \\ \vdots & \vdots & \vdots & \vdots \\ x & x & \ddots & x \end{bmatrix}$$

where x denotes an unrestricted nonzero element. There are $q(q-1)/2$ exclusion restrictions and H is exactly identified. The above identification strategy is analogous to achieving exact identification by ordering the variables in a standard VAR in a particular Wold causal chain, although the main difference is that in this setting we have the additional idiosyncratic innovation u_t.

To estimate the matrix H, we follow the Stock and Watson [100] approach, meaning that $B^*_{0:K}\epsilon_t = B_{0:K}e_t$ implies $B^*_{0:K}B^{*\prime}_{0:K} = B_{0:K}\Sigma_e B'_{0:K}$, where $B_{0:K}$ contains the first K rows of $B_0 \equiv B(0) = \Lambda$, $B^*_{0:K} = B_{0:K}H^{-1}$, and Σ_e is the covariance matrix of e_t. Since $B^*_{0:K}$ can be obtained by performing a Choleski decomposition of $(B_{0:K}\Sigma_e B'_{0:K})$,i.e. $B^*_{0:K}$=Chol$(B_{0:K}\Sigma_e B'_{0:K})$. It follows that $H = (B^*_{0:K})^{-1}B_{0:K}$, or

$$H = [Chol(B_{0:K}\Sigma_e B'_{0:K})]^{-1}B_{0:K}. \tag{2.11}$$

To estimate H, we need to replace $B_{0:K}$ and Σ_e with their estimates in Equation 2.11.

The impulse responses to structural shocks in ϵ_t are obtained using Equation 2.9. The identification procedure is similar to the standard recursive identification in VAR models,except that the series-specific term v_t is no longer existing in VARs. By imposing $K(K-1)/2$ restrictions, we just-identify the K structural shocks.

2.3.4 Partial Identification via block lower-triangular exclusion restrictions

Bernanke et al. [12] introduce a scheme for identifying a single shock in a structural FAVAR by adopting a block lower triangular structure for B_0^*. They partition the structural shocks and variables into three groups, slow variables, an interest rate and fast variables. The model they consider is the following:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + e_t \tag{2.12}$$

$$X_t = \Lambda^F F_t + \Lambda^Y Y_t + u_t \tag{2.13}$$

where F_t contains K latent factors and Y_t has M observable series. In the case of the two-step estimation procedure, the issue is to separate the space spanned by observable and unobservable factors. There are two different approaches to proceed with the estimation, which however yield almost identical results in the current exercise;

In the first approach, following Bernanke et al. [12], Y_t contains the Monetary Policy Interest Rate. As these authors, the sample is divided into a block of 'slow moving' series that do not respond immediately to a shock on the monetary policy interest rate, and another consisting of 'fast moving' variables that are not restricted. The latent factors are obtained from the following steps: (i) Let $\hat{C}(F_t, Y_t)$ be the K principal components of X_t (ii) Let X_t^S be the subset of "slow moving" variables. Let $C^*(F_t)$ be the K principal components of X_t^S (iii) Define $F^t = \hat{C}(F_t, Y_t) - \hat{\beta}_Y Y_t$, where $\hat{\beta}_Y$ is obtained by least squares estimation of the regression $\hat{C}(F_t, Y_t) = \beta_C C^*(F_t) + \beta_Y Y_t + \alpha_t$ (iv) Get the loadings by regressing X_t on F_t and Y_t.

In the second approach, Boivin, Giannoni and Stevanovic [15] estimated the latent factors through an iterative application of the principal components estimator. Starting from an initial estimate of F_t, F_t^0 which is the K first principal components of X_t: (i) Regress X_t on F_t^0 and Y_t to obtain $\hat{\Lambda}^{F,j}$ and $\hat{\Lambda}^{Y,j}$; (ii) Compute $\tilde{X}_t^j = X_t - \hat{\Lambda}^{Y,j} Y_t$; (iii) Update F_t as the first K principal components of $\tilde{X}_t$. The main advantage of this procedure is that it does **not** rely on any temporal assumption between the observed factors and the informational panel. By construction, F_t is contemporaneously uncorrelated with Y_t.

In both cases, the identification of structural shocks is achieved by imposing a recursive structure on the VAR residuals of 2.13. In our framework, following the first approach of Bernanke et al. [12], Y_t contains a proxy for the external finance premium and may contain other observable variables depending on the model specification;

Y_t can contain a credit spread and the Monetary Policy Interest rate, taking into account different orderings of Y_t (namely FAVAR1) Y_t can also contain different number of latent factors (namely FAVAR2), Y_t can contain only **one** of the credit spreads (namely FAVAR3).

2.4 Data and Model Specifications

Within this framework, there are different model specifications that are applied involving very different identifying restrictions and as well as an increasingly large number of economic and financial indicators. The time span for all panels starts in January 2000 and ends in December 2012 using monthly frequency. All series are initially transformed to induce stationarity. The description of the series, their transformation and the data resources are presented in the Appendix A.

Common proxies of the external finance premium of borrowing firms are the credit spreads for non-financial institutions. The data comprising this study is monthly and includes the yields on Markit iBoxx Euro Corporate Indices and Markit iBoxx Euro derived by the Deutche Bank website,as described in Appendix A. The data set used covers the European bond market, which is a market with unique characteristics and dynamics. This is mainly due to the introduction of the Euro as a single currency and the introduction of Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia and Slovenia as new member states in 2004. The introduction of the single currency provided the means to reshape the mechanics of the European financial markets, by liberating vast inflows of fragmented capitals under the different currencies, and providing the means for cross-border investments around a unified legislative framework which promoted the economic expansion of the single market, making it the largest fixed income economy in the world. The credit spreads (CS) are computed as the difference between the yield of the iBoxx Euro Corporate Index and the yield of the iBoxx Euro. The inclusion of the iBoxx indices in this study was decided on the premise that they would provide accurate and high quality bond prices. These indices are used as a proxy for the underlying market and serve as a basis for derivative products and portfolio valuation. At the same time, especially during the credit crisis period, they appeared to have gained safe-haven status in international financial markets so it was the best available proxy for the Euro Area credit market indicator.

In the main specification, we consider a monthly balanced panel containing 140 monthly Euro Area economic and financial series. We impose a recursive structure on the following four economic indicators: [C P I, U R, EONIA, CS]. This assumption implies that the inflation rate based on the consumer price index (CPI), the unemployment rate (UR) and the Euro OverNight Index Average (EONIA)[2] are the only indicators that do not respond immediately to a surprise increase in the respective credit spread measure,

[2]Throughout the text, we will always refer to the policy variable as the ECB policy rate. Nevertheless, it should be clarified that, in the empirical exercise, we have followed the strategy usually used in the VAR literature and have preferred to use an effective rate instead of the target rate itself. In this way, we have considered the Euro OverNight Index Average (EONIA) as a proxy for the effective monetary policy rate. The EONIA is the effective overnight reference rate for the euro area and is computed as a weighted average of all overnight unsecured lending transactions undertaken in the interbank market, initiated within the euro area by the banks belonging to the contributing panel. The EONIA is the interbank rate that follows more closely the ECB policy rate and one of the ECB's aims is to contribute to the smooth path of this market rate. In our sample period, the EONIA was, on average, five basis points higher than the ECB policy rate. This reduced spread reinforces our idea that the EONIA rate might be the best proxy for the policy variable.

which is interpreted as the credit shock and that the EONIA will lead the responses. This identification scheme is related to the identification strategy in Gilchrist, Yankov and Zakrajsek [63] in the sense that the shock is seen as an unexpected increase in the external finance premium. However, it is important to remark that all indicators other than CPI, UR and EONIA may respond contemporaneously to the credit shock. In particular, we do not impose that all the measures of economic activity, prices and interest rates respond only with lag to the credit shock. Furthermore, the shock in our approach is a disturbance to the last element of the vector ϵ_t in Equation 2.9. It captures the surprise innovation in the CS measure, after accounting for fluctuations in past common factors as well as in the current factors that explain the behaviour of CPI, UR, and EONIA. The impact response of the CS measure is equal to the standard deviation of the credit shock, which is a function of the relevant factor loadings and the corresponding elements in the rotation matrix H in Equation 2.11.

2.5 Estimation results

2.5.1 Interpretation of factors

In this section, we attempt to highlight that the static factors are identified only up to orthogonal rotations, which is a feature that hampers their economic interpretation. However, even if the factors are not uniquely identified, from a theoretical point of view, when the sample size has a large enough N dimension (140 variables in our case), the estimated factors span the same space as the true factors, and therefore even if the estimated factors do not coincide with the driving forces of the economy, linear combinations of them do, as Marcellino, Stock and Watson [80] have proven. With this caveat in mind, we proceed with a tentative interpretation of the estimated factors. Table 2.1 portrays the higher five coefficients of correlation between each of the four factors and the variables included in our data set.

While it is a well documented fact in the empirical literature that the common factors are considered to capture an important dimension of the business cycle movements in most of the indicators, it remains an interesting question to be addressed and this is related to their economically meaningful interpretation. Another significant feature of the above mentioned identification approach is that it allows us to obtain the rotation matrix H which can be used to interpret the estimated factors. Recall from Section 2.2.4, that structural shocks are a linear combination of residuals, $\epsilon_t = He_t$.

Using this hypothesis, we can rewrite the system in its structural form:

$$X_t = \Lambda^* F_t^* + u_t \tag{2.14}$$

$$F_t^* = \Phi^*(L) F_{t-1}^* + \epsilon_t \tag{2.15}$$

where $F_t^* = HF_t$, $\Lambda^* = \Lambda H^{-1}$ and $\Phi^*(L) = H\Phi(L)H^{-1}$. As a consequence, given the estimates of F_t and H, we can obtain an estimate of the structural factors, $\hat{F}_t^* = \hat{H}\hat{F}_t$, associated with the structural shocks ϵ_t. Table 2.1 presents the correlation coefficients between the estimated rotated factors, F_t^*, and the variables used in the recursive identification scheme. The results reveal that the rotation by $\hat{H}$ yields estimated structural factors that are very close to the observed indicators used in the recursive identification scheme: the first rotated factor is highly correlated with CPI, the second is related to the unemployment rate, the third to the EONIA and the last to our credit spread measure.

More specifically, the first estimated factor mainly captures the real side of the euro area economy, as it shows a higher than 90% coefficient of correlation with real GDP and Gross Value Added (GVA) as well as with real imports and exports of goods and services. The second latent factors mostly capture cyclical variations in inflation as displayed by the high correlation with the deflator of private consumption, the labour costs and the producer price index and with the GDP and GVA deflators, compensation per employee and some components of the HICP. The third estimated factor resembles very closely the behaviour of nominal interest rates, showing a correlation close to 75% with the Euribor rates.

2.5.2 Variance Decomposition

Forecast error variance decomposition is another exercise frequently performed when assessing the VAR results. It consists of determining the portion of the variance of the forecasting error of a variable, at any period t, that is attributable to a given shock and it follows immediately from the coefficients in the moving average representation of the VAR system and the variance of the policy shocks (see Bernanke et al. [12]). It must be noticed that the FAVAR approach potentially provides a more accurate variance decomposition than the VAR approach because the relative importance of the policy shock is assessed only to the portion of the variable explained after removing the idiosyncratic component.

Let $\hat{X}_{t+h|t}$ be the optimal h-period ahead forecast of X_{t+h} on date t information and $X_{t+h} - \hat{X}_{t+h}|t$ the forecast error. The fraction of the variance of the forecast error that is due to the credit shock, ϵ^{CS}, may be expressed as:

$$\frac{Var(X_{t+h} - \hat{X}_{t+h|t}|\epsilon^{CS})}{Var(X_{t+h} - \hat{X}_{t+h|t})} \tag{2.16}$$

Tables 2.3 - 2.5 report the results for the same 17 macroeconomic variables analysed previously for all the three different FAVAR specifications. The first two columns of the tables report the contribution of the credit shock for the variance of the forecast error of each of the variables, at the 6-month horizon and the 60-month horizon, respectively. In order to access the goodness of fit properties of the estimated factors, the last column of the tables report the R^2 of the regression of each of the 17 variables on the common factors $\hat{C}(F_t, Y_t)$, i.e. the fraction of each variables' variance that is explained by both $\hat{F}_t$ and Y_t. A high R^2 indicates that the common factors nicely summarise the information contained in the variable, whereas a low R^2 means that the variable cannot be adequately explained by the common factors and implies that we must have less confidence in the impulse responses and forecast error variance decomposition computed. There is an agreement in the literature that credit shocks account for only a very modest percentage of the volatility of output and for even less of the movements in the price level, so they can affect the economy mostly through its systematic behaviour, rather than by surprising economic agents. In fact, looking at Table 2.3, we infer that at the 6-month horizon, apart from interest rates, the contribution of the shock is lower than 5%. In particular, between $1-2\%$ of the total variance of both GDP and HICP is accounted for by the shock. After 60 months, the credit spread shock explains around 38% and 19% of the volatility of GDP and industrial production, respectively, and about 3% of price volatility. In addition, the shock accounts for 10% and 9% of the variance of the prediction error of consumption expenditure and employment, respectively. Overall, these results suggest a non-negligible role for the unsystematic component of credit spreads in affecting the dynamics of both real and nominal variables. On the other hand, an analysis of the last column of Table 2.3 reveals that the common component explains an important portion of the variance of some variables. Specifically, we obtain an R^2 of 87.1%, 78.7%, 54%, 71.9%, 48.7% and 87.2% for the GDP, industrial production, HICP, employment, nominal effective exchange rate and the Producer Price Index, respectively. However, there are also some variables for which the R^2 is small, in particular the money aggregate M3 (23.8%).

2.5.3 Impulse Response Functions Analysis

Following Equation 2.1 in section 2.3, the impulse responses of the estimated factors and of the variables observed included in Y_t are computed as follows:

$$\begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \hat{\delta}(L)\epsilon_t \tag{2.17}$$

where $\hat{\delta}(L) = [\hat{\Phi}(L)]^{-1} = \hat{\delta}_0 - \hat{\delta}_1(L) - \cdots - \hat{\delta}_h L^h$ is a matrix of polynomials in order h in the lag operator L and $\hat{\delta}_j$where $j = 0, 1, \ldots, h$ is the coefficient matrix.

Using Equation 2.2, the estimator of X_t is, $\hat{X}_t = \hat{\Lambda}^f \hat{F}_t + \hat{\Lambda}^y \hat{Y}_t$ and the impulse-response functions of each variable included in X_t can be obtained as follows:

$$X_t^{IRF} = \begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \hat{\delta}(L)\epsilon_t \tag{2.18}$$

Figures 2.1, 2.2, 2.3 depict the impulse responses of a subset of 20 key variables to the credit spread innovation for our baseline (namely FAVAR1) and the two alternative FAVARs (FAVAR2, FAVAR3), respectively. The corresponding 90% confidence intervals (dashed lines) were calculated using a standard bootstrap procedure with 5,000 iterations, as explained earlier. It must be stressed that although we only display responses for a small subset of variables, impulse responses can be generated for all the variables included in the panel making use of Equation 2.18. This is so because all the variables included in the data set can be represented as linear combinations of the estimated factors ($\hat{F}_t$ and Y_t) plus idiosyncratic noise. The responses in Figures 2.1, 2.2, 2.3 are very similar and have in general the intuitive sign and magnitude as described in the financial accelerator literature, implying that all the three different model specifications have little impact on the derived impulse responses analysis. However, there are also some counterintuitive responses for some variables.

An unexpected credit spread shock results in a gradual decrease in industrial production, which reaches its maximum effect after around two years, before reverting to the baseline scenario. The shape of the response is similar to that of the real GDP, but the magnitude is higher, since an unexpected 25-basis-point increase in the credit spread has a maximum impact on industrial production of more than one per cent in all the three formulations. When we split the analysis of the industrial production index, we find out that this strong response is mainly explained by the behaviour of durable consumer goods, since the impact of the disturbance on nondurable consumer goods is rather more modest. In its turn, capacity utilisation reaches its maximum decline roughly two years after the monetary tightening, after which it eventually returns towards zero. The reaction of consumption expenditure is also in line with expectations, in the sense that a higher short-term interest rate makes financing more expensive, leading to a decrease in private consumption, with the maximum impact (0.2% in the baseline FAVAR) being reached around 20 months after the shock. Also as expected, total employment falls after the disturbance but this movement is also not very persistent, and starts to revert two years after the shock.

The behaviour of retail trade and business sentiment indicators is also in line with theory, since a wider credit spreads have a negative impact on these variables, but that eventually fades out. This is also true for the producer price index for industry and the ECB commodity price index. Nevertheless, in spite of the expected shape of the response of the commodity price index, the magnitude of the response is much higher than expected, and therefore has to be interpreted with caution. Short-term interest rates such as the 6-month Euribor follow the official interest rate very closely, while longer-term interest rates such as the 10-year Government bond yield, although lying closely to the path of the official rate, show responses of a minor magnitude. Money aggregates go down in the medium term and tend towards the zero line in the long run. The decline in money aggregates reflects the decrease in demand for credit as a consequence of the higher refinancing costs resulting from higher interest rates. It should be noted, however, that all figures reveal that there is a slight increase in the first four/five months after the shock, and only then does the expected fall occur. A potential argument to explain this result could be that the money growth is dampened in the long run but that in the short run money aggregates (for example M3) may increase due to portfolio shifts (if the yield curve is flat, investments in short-term financial assets, which are part of M3, become more attractive than longer-term investment exposures, which are not part of money).

Moreover, the extra information generated by the FAVAR approach brings to light some interesting results as regards the responses of the components of the HICP. In fact, it seems that the intuitive negative response of inflation (total index) is strongly driven by the component energy and unprocessed food, which shows a big decrease after the shock. However, when we look at the response of the HICP excluding energy and unprocessed food, we see that after an initial fall in the first five months following the shock, the prices start to increase (the magnitude of the response is not very relevant as the maximum impact is of 0.03% in the first alternative FAVAR, but it nevertheless constitutes a puzzle). One could find the strong response of the component energy and unprocessed food somewhat surprising, in particular taking into account that VAR models typically rest on the assumption that prices are sticky. However, as Boivin, Giannoni and Mihov [16] draw attention to, recent evidence on the behaviour of disaggregated prices suggests that prices are much more volatile than conventionally assumed in studies based on aggregate data. The authors even prove that flexibility of disaggregate prices is perfectly compatible with stickiness of aggregate price indexes and that goods with little value added in final production, that is, energy-related good and fresh foods, display much more frequent price changes than the remaining components or price indexes. It must also be pointed out that, as expected, the response of the component energy and unprocessed food is very similar to the response of the producer price index, as shown in the impulse response functions. Our analysis also reveals a counterintuitive response of the nominal effective exchange rate and the Euro/US dollar exchange rate (both defined in indirect quotation). In fact, in all FAVAR specifications, a widening in the credit spread is associated with an initial depreciation of the euro, and this is against the economic rationale that a higher interest rate makes investment more attractive and therefore attracts capital inflows, causing the euro to appreciate. Moreover, we believe that this result may be related to the fact that our sample encompasses the most acute phase of the world financial crisis (after September 2008) that was fuelled by the problems in the US subprime market. In fact, both the US Federal Reserve (FED) and the European Central Bank (ECB) started to cut their official interest rates after the beginning of the turbulence and during this period the euro appreciated against the US dollar, which is in fact an intuitive response for the easing of the US monetary policy (i.e. as expected, the US dollar depreciates as a result of the decrease in US official interest rates). It must also be noticed that, in October 2008, the ECB introduced a number of changes to its monetary policy framework. In particular, until this date, the ECB used to conduct its refinancing operations through variable rate tenders in which the amount allotted was that corresponding to the amount bid at rates equal to or above the marginal rate. After October 2008, the ECB started to provide an unlimited amount of funds through its refinancing operations, which it began to conduct via fixed rate tenders at a rate equal to the policy rate and with full allotment. As the interbank money market practically stopped functioning during the financial crisis and as a consequence of the change in the Eurosystem's operational framework, the ECB became the preferred counterparty, with credit institutions resorting heavily to its tenders to obtain the funds needed, and therefore short-term liquidity conditions turned out to be very ample. Consequently, the EONIA rate fell considerably and stopped mimicking so well the behaviour of the ECB policy rate. An extension of our sample in the future, in particular encompassing observations after the end of the crisis, may be needed to understand if it changes in a relevant way the impulse responses of the economic variables (and in particular if it cancels out the counterintuitive results of the impulse responses of the exchange rates).

2.5.4 Uncertainty of impulse response functions

The analysis could be completed with the comparison of the precision of the impulse responses. Table 2.2 presents the standard errors for the responses of the EONIA interest rate, GDP and inflation to a one-standard-deviation innovation in the credit spread, for each of the three specifications under analysis. It must be noticed that, as Bernanke et al. [12] also highlighted, the two-step approach used to estimate the FAVARs suffers from generated regressors problem in the second step of the suggested methodology. In this way, the standard errors delivered by the usual econometric packages tend to underestimate the degree of uncertainty of responses, since they are computed on the assumption that the regressors included in the VAR are observed, which is not our case, as the factors are latent variables, which can partially explain the statistically insignificant results. In order to reduce these effects, the standard deviations for all the different FAVARs were calculated using a standard bootstrap procedure, with 5,000 replications, which accounts for most of the uncertainty in the factor estimation. The results depicted in Table 2.2 confirm that the benchmark FAVAR presents the lowest precision of responses for any of the three variables (but mostly for output and inflation). The additional information delivered by the factors seems to reduce the uncertainty of responses, the first alternative FAVAR being the one showing lower standard deviations, followed by our baseline FAVAR specification, except for HICP of the FAVAR3 that is better than the baseline.

2.5.5 Robustness Check

We have performed two types of robustness tests for the results of our preferred FAVAR specification. As a first step, the results were checked for robustness to changes in the number of factors (the number of factors was reduced to three, the number used in a similar exercise for monetary policy shocks for the US economy). As a second step, we have treated the EONIA rate as an exogenous variable in order to work out if the responses change in a noteworthy way. The results for the the two robustness exercises are depicted in Table 2.4 and Table 2.5 respectively. In both cases, the observed changes in the impulse response analysis are not significantly different than in the first FAVAR specification implying that choosing a large number of factors does not contribute significantly to the better explanation of the propagation mechanism of the credit shocks under analysis. Finally, considering the interest rate to be an exogenous variable does not alter our results in a noteworthy way. In both specifications, we still obtain considerable R^2 for the majority of the variables, and a low R^2 for the money aggregate. In the first robustness check, the shape and magnitude of the responses does not change in a very significant way, although the return to baseline is slower for most of the variables. However, the exception worth mentioning is the behaviour of the HICP, as when we reduce the number of factors, the price puzzle starts to be visible. This is not very surprising, if we take into account that according to the tentative interpretation of the factors performed, both the second and the fourth latent factors seem to capture cyclical variations in inflation and we are not considering the latter in this exercise. In the second robustness test, although the magnitude of the responses does not change in a very relevant way, the effects are even more long-lasting than in the first test, which might suggest that when EONIA is treated as endogenous, it can absorb partially the effects on the other variables of the system.

2.6 Concluding remarks

In this paper, we provide evidence on the propagation mechanism of credit shocks to economic activity. The framework under analysis exploits the dynamics of an extensive dataset of financial and economic indicators using several specifications of a structural factor model. The structural shocks were identified by imposing a minimum set of restrictions on the matrix of impact responses of several economic indicators. The common factors are shown to explain an important fraction of the variability in many observable variables and implying that they are able to capture a sizeable dimension of the business cycle.

Moreover, the suggested identification strategy allows us to recover underlying structural factors which have an interesting economic interpretation. A variance decomposition analysis suggests that credit shocks have important effects on several real activity measures, price indicators, leading indicators, and credit spreads. The results show that an unexpected increase of a measure of the external finance premium generates a statistically and economically significant economic downturn.

This downturn is persistent and results in a significant increase in the unemployment rate and a gradual decrease in price indices. Leading indicators including interest rates and measures of confidence respond strongly and significantly on impact of the unexpected credit shock. The underlying identification strategy, by imposing the minimum of identification assumptions, allows most of the indicators to respond contemporaneously to the shock and as a result yields a more realistic and economically meaningful picture of the effects of credit shocks on the economy.

Correlation between the factors and the data set

	Top-5 Coefficients of Correlation	
	Exports	0.944***
	GDP	0.941***
Factor 1	Labour Productivity - Total	0.941***
	Gross Value Added	0.921***
	Imports	0.912***
	Deflator Private Consumption	0.798***
	Labour Costs Construction	0.744***
Factor 2	Labour Productivity - Construction	0.709***
	Capacity Utilisation	0.609***
	Producer Price Index - Manufacturing	0.581***
	REFI	0.763***
	EURIBOR3MD	0.755***
Factor 3	EURIBOR1YD	0.742***
	EONIA	0.713***
	3Y.YLD	0.631***
	5Y.YLD	0.687***
	EURIBOR6MD	0.632***
Factor 4	3-5CORP	0.629***
	EURIBOR3MD	0.617***
	1-3CORP	0.587***

TABLE 2.1: *** denotes statistical significance to the 1% level.

	EONIA	GDP	HICP
Baseline FAVAR1	0.026	0.041	0.025
Alternative FAVAR2	0.022	0.038	0.023
Alternative FAVAR3	0.027	0.044	0.024

TABLE 2.2: Standard errors for the responses to a Cholesky (degrees-of-freedom adjusted) one-standard-deviation monetary policy innovation (average over 60 periods after the shock)

Forecast error variance explained by the credit shock; FAVAR with EONIA and the Credit Spread as exogenous variables.

	Variance Decomposition		
Variables	6 months	60 months	R^2
EONIA	0.202	0.191	1.000
	(0.081)	(0.081)	
GDP	0.012	0.381	0.871
	(0.018)	(0.128)	
HICP	0.021	0.030	0.540
	(0.024)	(0.072)	
IPIT	0.010	0.193	0.787
	(0.013)	(0.082)	
IP - Durable Consumer Goods	0.002	0.102	0.701
	(0.012)	(0.118)	
10-year German Bond Yield	0.285	0.163	0.632
	(0.070)	(0.074)	
M3	0.068	0.041	0.238
	(0.037)	(0.082)	
Nominal Effective Exchange Rate	0.004	0.058	0.487
	(0.049)	(0.134)	
Unemployment rate	0.087	0.138	0.698
	(0.028)	(0.088)	
ECB Commodity Price Index	0.006	0.094	0.321
	(0.029)	(0.087)	
Producer Price Index - Industry	0.018	0.094	0.872
	(0.012)	(0.120)	
Capacity Utilisation	0.021	0.028	0.512
	(0.021)	(0.074)	
Consumption Expenditure	0.004	0.108	0.516
	(0.021)	(0.071)	
Employment	0.021	0.092	0.719
	(0.028)	(0.123)	
Retail Trade	0.051	0.184	0.061
	(0.131)	(0.147)	
Business Climate Indicator	0.017	0.099	0.470
	(0.040)	(0.158)	
EURIBOR3MD	0.201	0.197	0.897
	(0.031)	(0.187)	

TABLE 2.3: The figures in the column under 6 months" ("60 months") report the fraction of the variance of the forecast error, at the 6(60)-month horizon, explained by the credit shock. The last column reports the fraction of the variance of each variable explained by both $\hat{F}_t$ and Y_t. Standard errors are shown in parentheses

Forecast error variance explained by the credit shock; FAVAR with reduced number of factors to three.

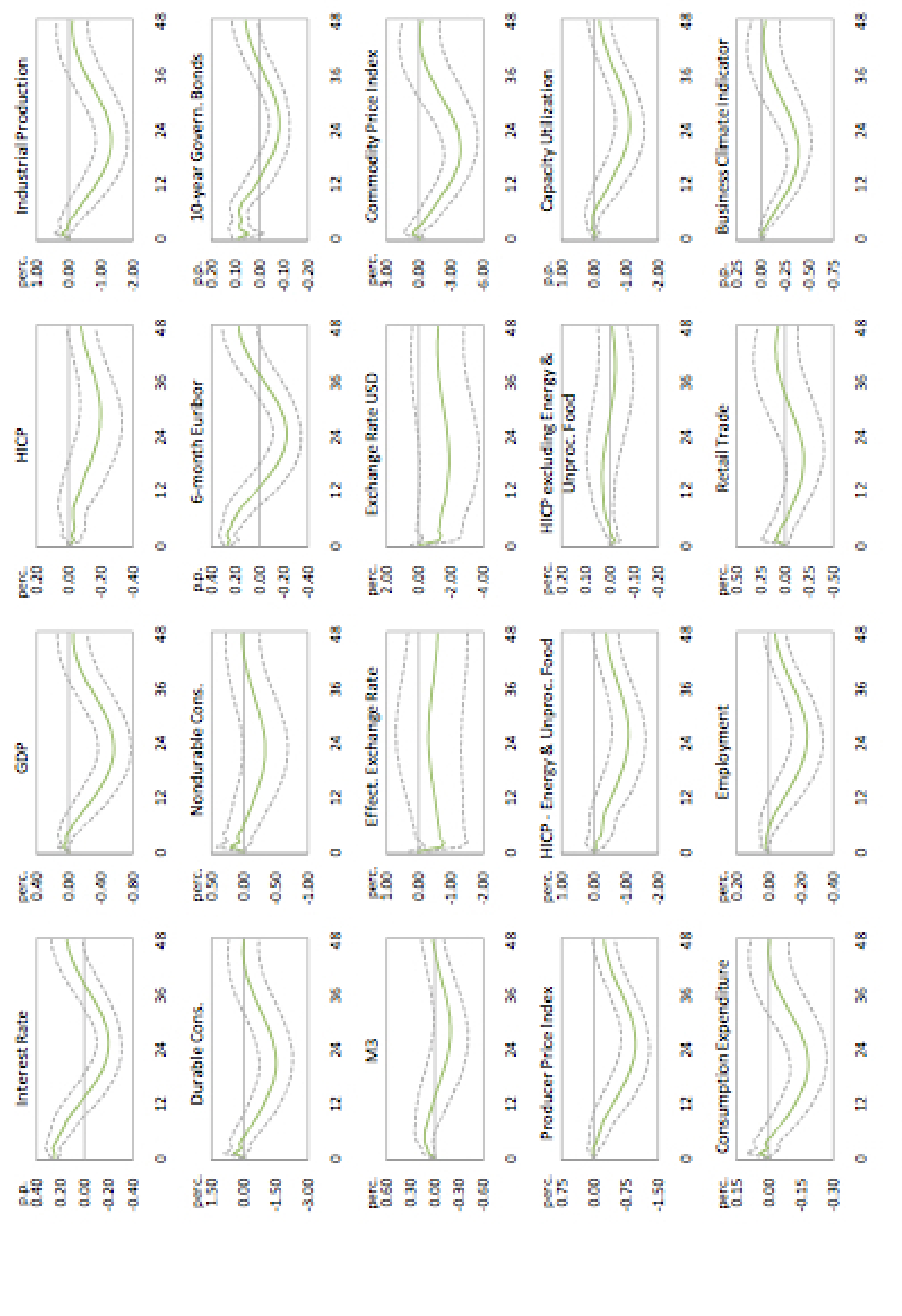
	Variance Decomposition		
Variables	6 months	60 months	R^2
EONIA	0.186	0.121	1.000
	(0.089)	(0.082)	
GDP	0.006	0.185	0.921
	(0.014)	(0.125)	
HICP	0.028	0.047	0.487
	(0.034)	(0.066)	
IPIT	0.013	0.118	0.634
	(0.028)	(0.065)	
IP - Durable Consumer Goods	0.001	0.038	0.691
	(0.014)	(0.035)	
10-year German Bond Yield	0.198	0.142	0.752
	(0.064)	(0.054)	
M3	0.067	0.034	0.256
	(0.087)	(0.069)	
Nominal Effective Exchange Rate	0.004	0.076	0.287
	(0.033)	(0.174)	
Unemployment rate	0.104	0.087	0.621
	(0.028)	(0.086)	
ECB Commodity Price Index	0.006	0.086	0.501
	(0.092)	(0.118)	
Producer Price Index - Industry	0.0196	0.056	0.862
	(0.010)	(0.093)	
Capacity Utilisation	0.011	0.028	0.396
	(0.031)	(0.066)	
Consumption Expenditure	0.003	0.128	0.583
	(0.018)	(0.068)	
Employment	0.018	0.104	0.637
	(0.031)	(0.106)	
Retail Trade	0.021	0.187	0.076
	(0.094)	(0.108)	
Business Climate Indicator	0.013	0.2981	0.301
	(0.021)	(0.123)	
EURIBOR3MD	0.201	0.197	0.917
	(0.031)	(0.187)	

TABLE 2.4: The figures in the column under "6 months" ("60 months") report the fraction of the variance of the forecast error, at the 6(60)-month horizon, explained by the credit shock. The last column reports the fraction of the variance of each variable explained by both $\hat{F}_t$ and Y_t. Standard errors are shown in parentheses

Forecast error variance explained by the credit shock; FAVAR with only the Credit Spread as exogenous.

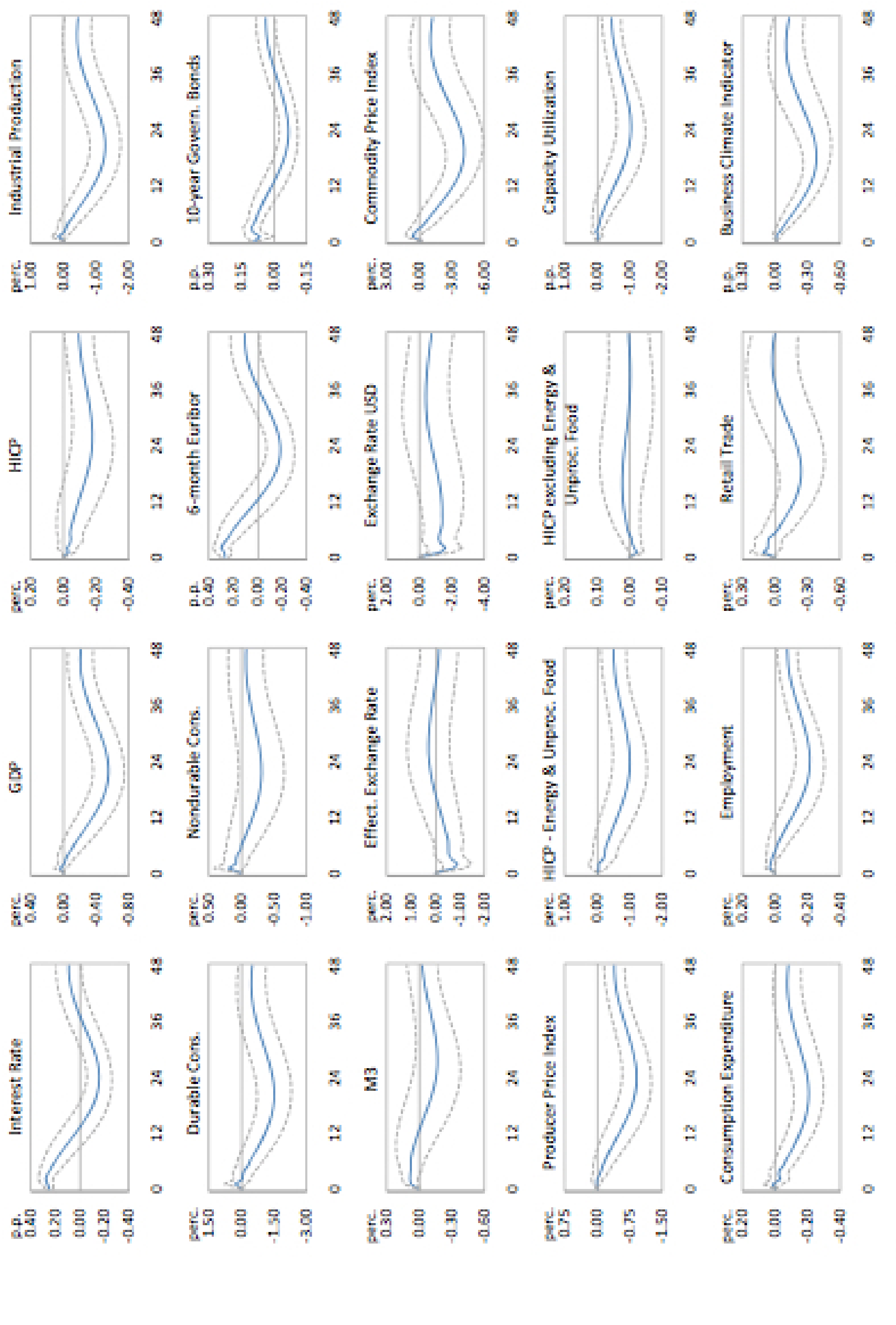
	Variance Decomposition		
Variables	6 months	60 months	R^2
EONIA	0.184	0.163	0.698
	(0.077)	(0.063)	
GDP	0.004	0.381	0.871
	(0.018)	(0.128)	
HICP	0.021	0.030	0.540
	(0.024)	(0.072)	
IPIT	0.010	0.443	0.787
	(0.013)	(0.109)	
IP - Durable Consumer Goods	0.002	0.301	0.701
	(0.012)	(0.118)	
10-year German Bond Yield	0.291	0.187	0.682
	(0.070)	(0.074)	
M3	0.074	0.038	0.245
	(0.049)	(0.073)	
Nominal Effective Exchange Rate	0.007	0.298	0.249
	(0.049)	(0.134)	
Unemployment rate	0.109	0.281	0.701
	(0.034)	(0.091)	
ECB Commodity Price Index	0.006	0.489	0.443
	(0.029)	(0.129)	
Producer Price Index - Industry	0.018	0.189	0.872
	(0.012)	(0.120)	
Capacity Utilisation	0.021	0.028	0.512
	(0.021)	(0.074)	
Consumption Expenditure	0.004	0.225	0.516
	(0.021)	(0.071)	
Employment	0.021	0.092	0.719
	(0.028)	(0.123)	
Retail Trade	0.051	0.289	0.061
	(0.131)	(0.147)	
Business Climate Indicator	0.017	0.341	0.470
	(0.040)	(0.158)	
EURIBOR3MD	0.201	0.197	1.000
	(0.031)	(0.187)	

TABLE 2.5: The figures in the column under "6 months" ("60 months") report the fraction of the variance of the forecast error, at the 6(60)-month horizon, explained by the credit shock. The last column reports the fraction of the variance of each variable explained by both $\hat{F}_t$ and Y_t. Standard errors are shown in parentheses



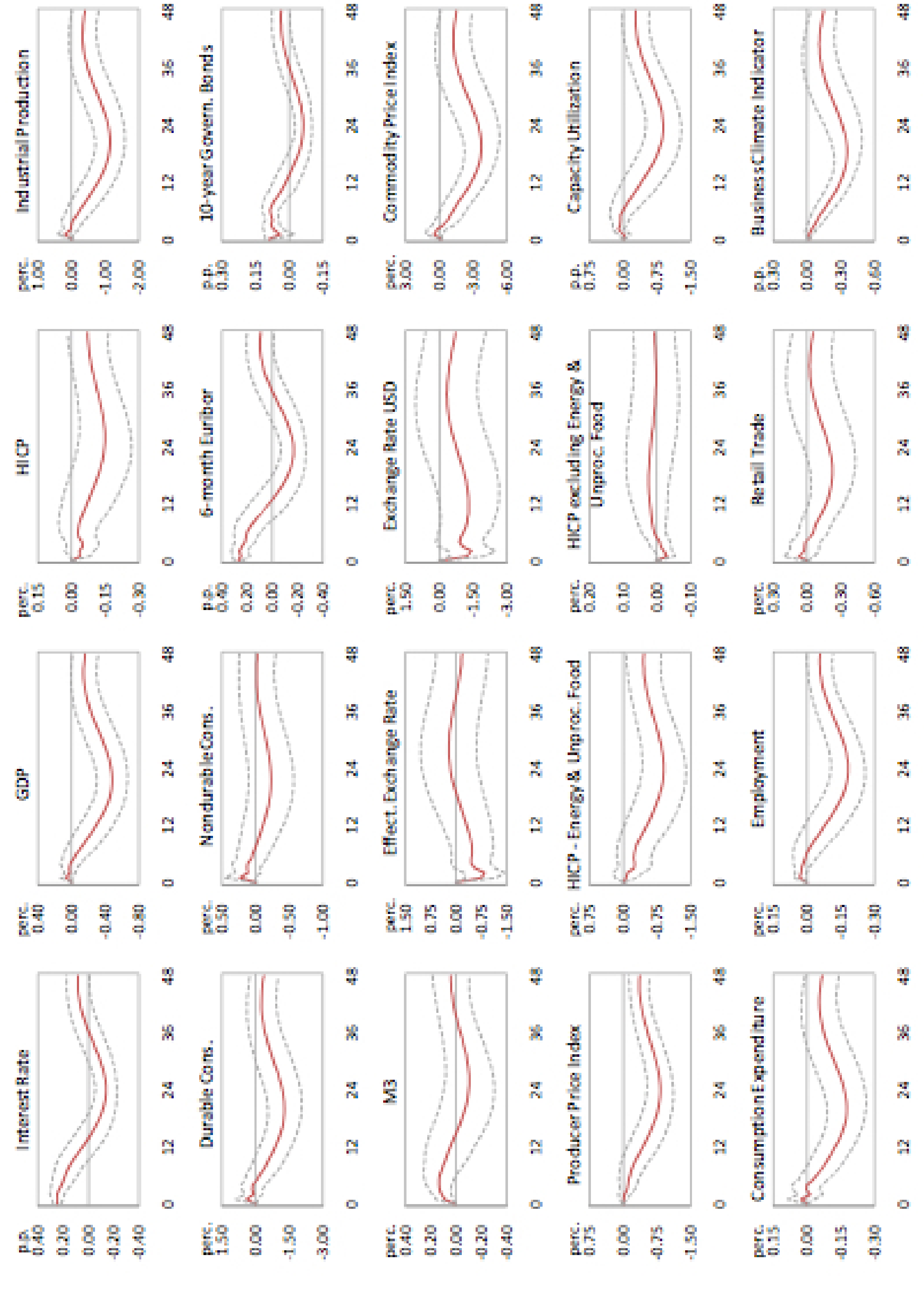
Notes: Percentage deviations from the baseline for variables for which logarithms were taken; percentage point deviations otherwise.

FIGURE 2.1: Impulse Response Functions for FAVAR1 .



Notes: Percentage deviations from the baseline for variables for which logarithms were taken; percentage point deviations otherwise.

FIGURE 2.2: Impulse Response Functions for FAVAR2 .



Notes: Percentage deviations from the baseline for variables for which logarithms were taken; percentage point deviations otherwise.

FIGURE 2.3: Impulse Response Functions for FAVAR3 .

Data Description and Transformation*

Nr.	Acronym	Description	Transformation
Real Output and Income			
1	IPIT	Industrial Production Index - Total(2005=100)	5
2	IPICOG	Industrial Production Index - MIG Consumer Goods (2005=100)	5
3	IPIDCOG	Industrial Production Index - MIG Durable Consumer Goods (2005=100)	5
4	IPINDCOG	Industrial Production Index - MIG non-Durable Consumer Goods (2005=100)	5
5	IPIING	Industrial Production Index - MIG Intermediate Goods (2005=100)	5
6	IPINRG	Industrial Production Index - MIG Energy (2005=100)	5
7	IPICAG	Industrial Production Index - MIG Capital Goods (2005=100)	5
8	IPIC	Industrial Production Index - Construction (2005=100)	5
9	IPIM	Industrial Production Index - Manufacturing (2005=100)	5
10	LCU	Level of Capacity Utilisation - Industry Survey	2
11	GDP	Gross Domestic Product at Market Prices (Chained)	5
12	GVA	Gross Value Added at Constant Prices (Chained)	5
13	PCEXP	Private Final Consumption Expenditure (Chained)	5
14	GCEXP	Government Final Consumption Expenditure (Chained)	5
15	GFKF	Investment - Gross Fixed Capital Formation (Chained)	5
16	EXP	Exports of Goods and Services (Chained)	5
17	IMP	Imports of Goods and Services (Chained)	5
Employment			
18	TOTEMPL	Total Employment (Thousands of persons)	5
19	TOTEMPLA	Total Employment - Agriculture (Thousands of persons)	5
20	TOTEMPLI	Total Employment - Industry (Thousands of persons)	5
21	TOTEMPLC	Total Employment - Construction (Thousands of persons)	5
22	TOTEMPLT	Total Employment - Trade (Thousands of persons)	5
23	TOTEMPLF	Total Employment - Financials (Thousands of persons)	5
24	TOTEMPLO	Total Employment - Other Services (Thousands of persons)	5
25	LP	Person Based Labour Productivity - Total (2000=100, constant prices)	5
26	LPA	Person Based Labour Productivity - Agriculture (2000=100, constant prices)	5
27	LPI	Person Based Labour Productivity - Industry (2000=100, constant prices)	5
28	LPC	Person Based Labour Productivity - Construction (2000=100, constant prices)	5
29	LPT	Person Based Labour Productivity - Trade (2000=100, constant prices)	5
30	LPF	Person Based Labour Productivity - Financials (2000=100, constant prices)	5
31	LPO	Person Based Labour Productivity - Other Services (2000=100, constant prices)	5
32	TOTUNEMPL	Standardised Unemployment Rate (%)	1
33	RUNLACO	Real Unit Labour Costs - Total (2000=100)	5
34	COMPEMPTOT	Compensation per Employee - Total Index (2000=100)	5
35	COMPEMPTOA	Compensation per Employee - Agriculture (2000=100)	5
36	COMPEMPI	Compensation per Employee - Industry (2000=100)	5
37	COMPEMPC	Compensation per Employee - Construction (2000=100)	5
38	COMPEMPT	Compensation per Employee - Trade (2000=100)	5
39	COMPEMPF	Compensation per Employee - Financials (2000=100)	5
40	COMPEMPO	Compensation per Employee - Other Services (2000=100)	5

*See Appendix A for the details of the Data resources and transformations

Data Description and Transformation (continued)

Nr.	Acronym	Description	Transformation
Prices			
41	CP00	HICP - All Items (2005=100)	5
42	CP01	HICP - Food and non-Alcoholic Beverages (2005=100)	5
43	CP02	HICP - Alcoholic Beverages, Tobacco and Narcotics (2005=100)	5
44	CP03	HICP - Clothing and Footwear (2005=100)	5
45	CP04	HICP - Housing Water, Electricity, Gas and other Fuels (2005=100)	5
46	CP06	HICP - Health (2005=100)	5
47	CP07	HICP - Transport (2005=100)	5
48	GOODS	HICP - Goods (2005=100)	5
49	SERV	HICP - Services (2005=100)	5
50	EFOODUNP	HICP - Energy and Unprocessed Food (2005=100)	5
51	00XEFOOD	HICP - Overall Index excluding Energy, Food, Alcohol and Tobacco (2005=100)	5
52	00XEFOODUNP	HICP - Overall Index excluding Energy and Unprocessed Food (2005=100)	5
53	00XHOUSING	HICP - Overall Index excluding Housing, Water, Electricity, Gas and other (2005=100)	5
54	PPIM	Producer Price Index - Manufacturing (2005=100)	5
55	PPII	Producer Price Index - Industry, Except Construction (2005=100)	5
56	PPICAG	Producer Price Index- MIG Capital Goods(2005=100)	5
57	PPIING	Producer Price Index - MIG Intermediate Goods (2005=100)	5
58	PPINDCOG	Producer Price Index - MIG non-Durable Consumer Goods (2005=100)	5
59	ECBCPI	ECB Commodity Price Index Euro Denominated - Total non-Energy,weighted (2000=100)	5
60	OIL	Oil Price, Brent Crude - 1 month forward (Level - EUR)	5
Exchange Rates			
61	EXRUS	Foreign Exchange Rate: United States of America (USD per EUR - monthly average)	5
62	EXRJP	Foreign Exchange Rate: Japan (JPY per EUR - monthly average)	5
63	EXRUK	Foreign Exchange Rate: United Kingdom (GBP per EUR - monthly average)	5
64	EXRSW	Foreign Exchange Rate: Switzerland (CHF per EUR - monthly average)	5
65	NEER	Nominal Effective Exchange Rate, 21 group of currencies (1999Q1=100)	5
Interest Rates			
66	REFI	ECB Official Refinancing Operation Rate (effective, %)	1
67	EURIBOR3MD	3-Month Euro Interbank Offered Rate (%)	1
68	EURIBOR6MD	6-Month Euro Interbank Offered Rate (%)	1
69	EURIBOR1YD	1-Year Euro Interbank Offered Rate (%)	1
70	3Y.YLD	3-Year Euro Area German Benchmark Bond Yield (%)	1
71	5Y.YLD	5-Year Euro Area German Benchmark Bond Yield (%)	1
72	7Y.YLD	7-Year Euro Area German Benchmark Bond Yield (%)	1
73	10Y.YLD	10-Year Euro Area German Benchmark Bond Yield (%)	1
74	EONIA	Euro OverNight Index Average	1
75	AAA	Markit iBoxx Euro Corporate Index AAA	5
76	AA	Markit iBoxx Euro Corporate Index AA	5
77	A	Markit iBoxx Euro Corporate Index A	5
78	A	Markit iBoxx Euro Corporate Index BAA	5
79	1-3CORP	Markit iBoxx Euro Corporate Index 1-3 years	5
80	3-5CORP	Markit iBoxx Euro Corporate Index 3-5 years	5
81	5-7CORP	Markit iBoxx Euro Corporate Index 5-7 years	5
82	7-10CORP	Markit iBoxx Euro Corporate Index 7-10 years	5
83	S3MDREFI	Spread EURIBOR3MD - REFI	1
84	S10Y.YLDREFI	Spread 10Y.YLD - REFI	1
85	S6MDREFI	Spread EURIBOR6MD - REFI	1
86	CS	Spread iBoxx EU Corporate-non Corporate	1
Stock Prices			
87	DJE50	Dow Jones Euro Stoxx 50 (2001=100)	5
88	DJE	Dow Jones Euro Stoxx Broad (2001=100)	5
89	DJEI	Dow Jones Euro Stoxx - Industrials (Points)	5
90	DJEU	Dow Jones Euro Stoxx - Utilities (Points)	5
91	DJEO	Dow Jones Euro Stoxx - Oil And Gas Energy (Points)	5
92	DJECG	Dow Jones Euro Stoxx - Consumer Goods (Points)	5
93	DJECS	Dow Jones Euro Stoxx - Consumer Services (Points)	5
94	DJEBM	Dow Jones Euro Stoxx - Basic Materials (Points)	5
95	DJETECH	Dow Jones Euro Stoxx - Technology (Points)	5
96	DJEH	Dow Jones Euro Stoxx - Healthcare (Points)	5
97	DJETEL	Dow Jones Euro Stoxx - Telecommunications (Points)	5
98	DJEF	Dow Jones Euro Stoxx - Financials (Points)	5
Money and Credit			
99	M1	Money Aggregate M1 (End of Period (Stocks))	5
100	M2	Money Aggregate M2 (End of Period (Stocks))	5
101	M3	Money Aggregate M3 (End of Period (Stocks))	5
102	MFICRINTGG	Credit to General Government (End of Period (Stocks))	5
103	MFICRINTOR	Credit to Other Residents (End of Period (Stocks))	5
104	CONSCREDIT	Consumer Credit (End of Period (Stocks))	5

Data Description and Transformation(continued)

Nr.	Acronym	Description	Transformation
Industrial New Orders			
Retail Turnover and Sales			
105	ORDM	Industrial New Orders - Manufacturing (2005=100)	5
106	ORDDCOG	Industrial New Orders - MIG Durable Consumer Goods (2005=100)	5
107	ORDING	Industrial New Orders - MIG Intermediate Goods (2005=100)	5
108	ITIM	Industrial Turnover Index - Manufacturing (2005=100)	5
109	ITICAG	Industrial Turnover Index - MIG Capital Goods (2005=100)	5
110	ITICOG	Industrial Turnover Index - MIG Consumer Goods(2005=100)	5
111	ITIDCOGD	Industrial Turnover Index - MIG Durable Consumer Goods(2005=100)	5
112	ITIING	Industrial Turnover Index - MIG Intermediate Goods (2005=100)	5
113	ITINDCOG	Industrial Turnover Index - MIG Non-Durable Consumer Goods (2005=100)	5
114	ITINRG	Industrial Turnover Index - MIG Energy (2005=100)	5
115	RTRADE	Total Turnover Index,Retail Trade excl.Fuel(2005=100)	5
116	RSALESFOOD	Total Turnover Index, Retail Sale of Food, Beverages and Tobacco (2005=100)	5
117	RSALESNFOOD	Total Turnover Index,Retail Sale of Non-Food Products (2005=100)	5
118	RSALESTEX	Total Turnover Index, Retail Sale of Textiles (2005=100)	5
119	RSALESHOUS	Total Turnover Index, Retail Sale of 2 5	
Balance of Payments			
External Trade			
120	BOPCUAC	BOP - Current Account (Net)	2
121	BOPKAC	BOP - Capital Account (Net)	2
122	BOPFAC	BOP - Financial Account (Net)	2
123	EXTTRADEIMP	External Trade - Imports - All Products,EA16	5
124	EXTTRADEEXP	External Trade - Exports - All Products,EA16	5
125	TOTRESING	Foreign Official Reserves (End of Period (Stocks))	5
Confidence Indicators			
126	BS-BCI	EA Business Climate Indicator	2
127	BS-ESI-I	Economic Sentiment Indicator	2
128	BS-CSMCI	Consumer Confidence Indicator	2
129	BS-ICI	Industrial Confidence Indicator	2
130	BS-RCI	Retail Confidence Indicator	2
131	BS-SCI	Services Confidence Indicator	2
Foreign Variables			
132	GDPUSA	USA - GDP (Chained Volume Estimates)	5
133	GDPUK	UK - GDP (Chained Volume Estimates)	5
134	GDPJP	Japan - GDP (Chained Volume Estimates)	5
135	CPIUSA	USA - CPI - All Items (2005=100)	5
136	CPIUK	UK - CPI - All Items (2005=100)	5
137	CPIJP	Japan - CPI - All Items (2005=100)	5
138	FFR	USA - Fed Funds Rate (Effective, %)	1
139	UKOBR	UK - Official Bank Rate (Target, %)	1
140	JPCR	Japan - Call Rate (Target, %)	1

Table 2.6: Data Description and Transformation - See Appendix A for details

Chapter 3

Multivariate time series models for exchange rate forecasting

3.1 Introduction

The literature on the out-of-sample predictability of exchange rates initiates with the study of Meese and Rogoff [87] in 1983 that, in their pioneering work, marked that standard exchange rate models could not outperform the simple random walk forecasting model. The authors ascribed the failure of the structural models to the failure of the goods market assumption (PPP assumption), money-demand equations and to the difficulties of predicting accurately the expected inflation rate. It is worth noting that the forecasts produced by the structural models, using the rolling regressions method, are based on the actual realised values of the future explanatory variables in order to avoid parameter uncertainty. This observed feature in the behaviour of exchange rates can be misleading since as Faust, Rogers and Wright [50] claimed any predictability that is found in such a model has limited usefulness to financial market analysts and policymakers who confront the unenviable task of forecasting exchange rates in real time. The very strong negative results of the Meese and Rogoff [87] study spawned an enormous amount of subsequent research that applied various econometric techniques or exploited the information set to try to rescue the ability of fundamental models to forecast exchange rates. Time-varying coefficients, expanded information sets or different functional forms were applied without great success. A parallel finding in the exchange rate literature, also dating from the beginning of 1980s, was that forward exchange rates are not good predictors of the future spot exchange rates movements, which implies that the forward premium is not an optimal predictor of the rate of depreciation, as suggested by the efficient market hypothesis, at least in its risk-neutral formulation. Since then and until now, vast literature has been evolved in order to investigate the source of this failure, either by focusing on the risk-neutral efficient markets hypothesis or on the rational expectations when applied to the foreign exchange market as a whole, without huge success. In theory, the relation between the spot and forward exchange rates is governed by the uncovered interest parity (UIP), which implies that the forward premium must be positively related to future exchange rates changes, although in practice this is not the case, since a negative relation is observed, as it was very well documented by Fama [49]. Assuming risk neutrality and rational expectations, UIP is the cornerstone condition for FX market efficiency.

Although more and more sophisticated econometric techniques were applied for improving the quality of results, empirical studies estimating the "Fama Regression" consistently reject the UIP condition (see Lewis [75] and Engel [45]). Consequently, it has now become a stylised fact that estimates of the β coefficient of the "Fama Regression" tend to be closed to minus unity than plus unity (see Froot and Thaler [58]). This negative value of the coefficient is the defining feature of what is widely known as the "forward bias puzzle", which basically implies the tendency of low-interest currencies to depreciate, when UIP would predict the opposite.

A ray of hope was provided by the study of Clarida and Taylor [33] in 1997, who show that even if the forward rate is not an optimal predictor of the spot rate, it still contains valuable information for explaining the spot rate. The key feature of this model framework is that forward premia still contain information pertinent to future spot rates changes, which implies that an appropriate way to exploit this information is through the estimation of the vector error correction models (VECMs) in spot and forward rates, rather than through single-equation methods. Using the above framework, the authors are able to extract sufficient information from the term structure of forward premia to outperform the random walk model for a range of exchange rates in out-of-sample forecast. Moreover, Clarida, Sarno, Taylor and Valente [32] proposed a term structure forecasting model of exchange rates which is based on a regime-switching vector equilibrium correction model and seems to forecast better than the linear VECM and the naive random walk model.

A parallel finding in the literature that provided a boost in the developments of econometric methods for the analysis of large datasets and is applied in the context of a factor model, started with the pioneering work of Stock and Watson [104] [98], where each of a large set of variables is split into a common component, driven by a very limited number of unobservable factors, and an idiosyncratic component. The basic idea is to extract information from the estimated factors for predicting future developments in as many variables as possible, by imposing a structure that summarises the information contained in a large set of predictors by focusing on some relevant linear combinations of them. If the number of principal components is smaller than the cross sectional dimension, this will reduce the dimensionality of our data set by seeking the underlying, unobservable variables which are reflected in the observed ones, by analysing the correlation matrix, leading to potential gains in out-of-sample forecasting. The main contribution in this strand of literature is made by Engel, Mark and West [46] that construct factors from a cross section of exchange rates and use the idiosyncratic deviations from the factors to forecast. They forecast using factors, and using factors combined with any of fundamentals suggested by Taylor rule, monetary and purchasing power parity (PPP) models. For long horizon (8 and 12 quarter) forecasts, they improve on the forecast of a "no change" benchmark in the late (1999-2007) but not early (1987-1998) parts of the sample.

An alternative approach, which also attempts to deal with the "curse" of dimensionality, applies a Bayesian Vector Autoregression (BVAR) approach, in which the VAR coefficients are shrunk towards a random walk representation. The most attractive feature of this model is that given the best forecasts of exchange rates are produced by a driftless random walk process, it is common sense to believe that exchange rates do follow such a process and it would be a good idea to incorporate such information in the model. Although a good forecasting performance of BVAR was documented years ago by Doan, Litterman and Sims [39] and Litterman [76], it was only in 2007 that Banbura, Giannone and Reichlin [18] and Carriero, Kapetanios and Marcellino [26] showed the effectiveness of such an approach for forecasting large information set and provided strong empirical evidence in favour of BVAR modelling.

Parallel to this literature, there is ongoing research arguing that the fact that the forward rate does not appear to be an optimal predictor of the future spot rate – that is, that Forward Rate Bias (FRB) exists and implies that it may be possible to exploit this market inefficiency in order to generate returns within investment portfolios in excess of underlying benchmark indices, including transaction costs of implementing the associated trading strategy. Lyons [77] and subsequently Della Corte, Sarno and Tsiakas [35], explain the profitability of the carry trade in terms of the presence of so-called limits to arbitrage and associated transaction cost thresholds that outweigh the welfare benefits of exploiting small deviations from UIP. Beyond these thresholds, UIP is demonstrated to hold. Also, Sager and Taylor [90] assess whether the Clarida -Taylor framework can be used to generate significant trading profits in combination with an acceptable degree of risk in a realistic portfolio context.

In this paper, I consider the task of forecasting the exchange rates by using a purely time series approach that exploits information in a rather large panel of exchange rates. Given that simple multivariate linear models suffer from dimensionality problem, it seems natural to apply methodologies that attempt to efficiently summarise the information contained in large datasets and at the same time to take advantage of the cross sectional information contained in such a dataset. For that reason, a large information set is used (a panel of 24 exchange rates) in order to estimate a Factor Model using Principal Components Analysis to extract the underlying, unobservable factors. From a forecasting point of view, the idea is to use the estimated factors for predicting future developments in all the variables/predictors under consideration. An alternative approach that attempts to summarise information from large datasets is also considered through the estimation of a Bayesian VAR model in which the VAR coefficients are shrunk towards a random walk representation in order to compare their forecasting performance against simple multivariate models. Although using a large dataset as predictors for a small number of key macroeconomic variables has been on top of the research agenda, it is not such a common practice to focus on forecasting all the variables of the dataset using multivariate time series models.

Forecasts for the full panel of 24 exchange rates against the US Dollar are generated and the empirical evidence is rather mixed; The Factor Model appears to outperform the alternative modelling strategy, the Bayesian VAR specification and sometimes against the naïve random walk at $1-$step ahead forecast but also to generate lower forecast errors when compared to it. On the other hand, the Bayesian VAR approach appears to systematically outperform against the simple AR and VAR alternatives, but also to generate more accurate predictions against the naïve random walk for some currencies, including forecast gains that arise at the $1-$step ahead forecast horizon, which has been proven to be the most challenging one, especially in the exchange rate forecasting literature. Finally, a trading strategy is being implemented to assess the economic value of the statistical models under consideration and overall the trading strategy based on the factor model generates positive returns.

The paper is structured as follows. Section 3.2 describes the Factor Model and the BVAR specification in details. Section 3.3 discusses the performed forecasting exercise and reports the results. Section 3.4 describes and discusses the applied trading strategies. Section 3.5 summarises and concludes.

3.2 Econometric Framework

In this section, the basic two econometric frameworks are described in details. The first is the Factor Model and the extraction of the principal components and the second involves the estimation of a Bayesian VAR Model with a driftless random walk prior.

3.2.1 Factor Model with Principal Components Analysis

Let y_t be the time series variables to forecast and X_t be an $N \times 1$ vector of observations at time t on a large number, N of possible predictors. Let F_t be an $L \times 1$ vector of unobservable factors, and Γ an $N \times L$ matrix of factor loadings. It is then assumed that (X_t, y_{t+h}) admit a factor model representation with r common latent factors F_t,

$$X_t = \Gamma F_t + \epsilon_t \tag{3.1}$$

and

$$y_{t+h} = \beta_F F_t + \beta_w w_t + \epsilon_{t+h} \tag{3.2}$$

where ϵ_t is a $N \times 1$ vector of idiosyncratic disturbances and w_t a $M \times 1$ vector of observed variables (in our case, lags of y_t) that along with F_t are useful for forecasting y_{t+h} with ϵ_{t+h} resulting forecast error. β_F and β_w are $N \times L$ and $N \times M$ matrices of unobservable and observable factor loadings coefficient matrices respectively. Data are available for $\{y_t, X_t, w_t\}_{t=1}^{T}$ and the aim is to forecast y_{t+h}.

If the idiosyncratic disturbances ϵ_t in Equation 3.2 were cross sectionally independent and temporally iid, then Equation 3.1 would be a classic factor model analysis. However, since this is a macroeconomic forecasting application,these assumptions are unlikely to be satisfied, so we can allow the error terms to be both serially and cross sectionally correlated, applying the usual exogeneity assumptions of Stock and Watson [96].

The dynamic relationship between (W_t, F_t) can be described using the following framework:

$$\begin{bmatrix} F_t \\ W_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ W_{t-1} \end{bmatrix} + \epsilon_t \tag{3.3}$$

where $\Phi(L)$ is a lag polynomial of finite order h and ϵ_t is a vector of independently and identically distributed errors.

Equations 3.2 and 3.3 above cannot be directly estimated, since F_t is unobservable. In the literature, there are several indirect ways of estimating unobservable factors, i.e. the Gibbs sampling approach, maximum likelihood or through a two-step procedure of principal components. In this paper, in order to identify the factors, the two-step approach suggested by Stock and Watson [104] [96] is followed, where the factors are first extracted as principal components and then taken as given for the estimation of the parameters of the model. More specifically, for the factor estimation, where the two-step principal components method was applied, the following eigenvalue problem for the sample covariance matrix was considered:

$$\Lambda_i Y_r^i = Y_r^i C_r^i \tag{3.4}$$

where Λ_i is the covariance matrix of the standarized data X_t^i, $Y_r^i = [y_1, \ldots, y_r]$ is the $(n_i \times r_i)$ matrix whose columns are the r_i eigenvectors corresponding to the first r_i largest eigenvalues of the covariance matrix and C_r^i indicates a diagonal matrix representing the first r_i largest eigenvalues. From this problem, the first r_i principal components are defined in the following way:

$$\hat{F}_t^i = Y_r^i\prime X_t^i \tag{3.5}$$

The number of factors retained should be large enough to account for the common variation in the sample, but at the same time, small enough to discard factors that mainly represent idiosyncratic movements in the data. As a result, the aim is to identify key developments behind exchange rates movements based on the notion that the covariance structure of the data contains important information to explain currency movements. Multivariate data can exhibit patterns, that imply a common structure in the data. The criterion applied here to identify the number of factors to be retained is the common Kaiser - Guttman criterion, which mentions that only factors with an eigenvalue larger than one should be retained.

In terms of the forecasting exercise using the above mentioned framework, we can apply the following two-step procedure. In order to construct y_{t+h}, we form principal components of $\{X_t\}_{t=1}^T$ to serve as estimates of the factors. These estimated factors,together with w_t,(lags of y_t) are then used in Equation 3.3 to estimate the regression coefficients. The forecast is constructed as $\hat{y}_{t+h} = \hat{\beta}_F \ F_t + \hat{\beta}_w w_t$, where $\hat{\beta}_F$, $\hat{\beta}_w$ and $\hat{F}_t$ are the estimated coefficients and factors. Under a set of moment and rank conditions the mean square error of the feasible forecast asymptotically approaches the one of the optimal infeasible forecast for N and T approaching infinity, as shown by Stock and Watson [104] [96]. Moreover, as it was shown by Stock and Watson [96], the feasible forecast $\hat{y}_{t+h}$ constructed from the estimated factors together with the estimated coefficients converge to the infeasible forecast that would be obtained if all the parameters were known.

3.2.2 The BVAR Model with the driftless random walk prior

A random walk without a drift is overall a very competitive model in forecasting exchange rates. As a result, it seems reasonable to build a forecasting model in which exchange rates *a priori* follow such a process. At the same time, the forecasting should also account for dynamic co movements in exchange rates. Bayesian methods allow to impose restrictions on the data, but also let the data speak. The exclusion restrictions are imposed as priors, so if some a-priori excluded variable turns out to be relevant in the data, the posterior estimate would contain it. This approach deals with the dimensionality problem since by including prior information we can more efficiently summarise the information contained in large datasets. I denote the exchange rate of a currency i vis-a-vis the US Dollar at time t as $y_{i,t}$ and I collect all the exchange rates in the $N-$dimensional vector $Y_t = (y_{1,t}, y_{2,t}, \ldots, y_{N,t})\prime$. We consider the following vector autoregression:

$$Y_t = \Phi_{0,h} + \Phi_{1,h} Y_{t-h} + \epsilon_t; \quad \epsilon_t \sim IIDN(0, \Psi) \tag{3.6}$$

In this paper, a Normal-Inverted Wishart version of the so-called Minnesota prior of Doan, Litterman and Sims [39] and Litterman [76] is implemented. This version of the prior was proposed by Kadiyala and Karlsson [69] and is computationally more efficient and avoids the inconvenient assumption of fixed and diagonal residual variance matrix. In the above mentioned model Y_t is regressed directly onto Y_{t-h} which means that for each forecast horizon, h, a different model is employed, i.e "direct" forecasting method is used. This approach mainly focuses on minimising the relevant loss function for each forecast horizon, meaning the $h-$step ahead forecast error, while the traditional 'indirect' forecasting strategy implies that the only loss function considered is based on the $1-$step ahead forecast error. The $h-$step ahead forecast produced by a driftless random walk forecast is $\hat{y}_{i,t+h} = y_{i,t}$. In order to construct a model that *a priori* produces such a forecast we need to impose that $\Phi_{0,h} = 0$ and $\Phi_{1,h} = I$. The restriction $\Phi_{0,h} = 0$ imposes the absence of drift, while the restriction $\Phi_{1,h} = I$ sets to zero all the coefficients except from the own lag in each equation, that is set to one and imposes in such a way a univariate random walk representation for each of the available variables.

The Minnesota prior shrinks parameter estimates towards a random walk representation and it has proven to be robustly good in forecasting. In particular, the prior expectations of $\Phi_1, \Phi_2, \ldots, \Phi_p$ under the Minnesota prior are:

$$E[\Phi_k^{(ij)}] = \begin{cases} 1 & \text{for } j = i, \forall k \\ 0 & \text{otherwise} \end{cases}$$

and

$$V[\Phi_k^{(ij)}] = \begin{cases} \phi\frac{1}{\kappa^2} & \text{for } j = i, \forall k \\ \phi\frac{1}{\kappa^2}\theta\sigma_i^2\sigma_j^{-2} & \text{for } j \neq i, \forall k \end{cases}$$

while the residual matrix Σ is fixed and diagonal: $diag(\sigma_1^2, \ldots, \sigma_N^2)$. The hyperparameter ϕ measures the overall tightness of the prior and the factor $\frac{1}{\kappa^2}$ is the rate at which prior variance decreases with increasing lag length while the ratio σ_i^2/σ_j^2 accounts for the different scale and variability of the data. Finally, the parameter θ imposes additional shrinkage on the coefficients attached to a regressor when it is not a lag of the dependent variable in a given equation. Kadiyala and Karlsson [69] proposed a version of this prior which allows to avoid the inconvenient assumption of a fixed and diagonal residual variance matrix and gain substantially in terms of computational efficiency at the cost of fixing $\theta = 1$. The prior then has a Normal-Inverted Wishart form:

$$\Sigma \sim IW(u_0, S_0); B \mid \Sigma \sim N(B_0, \Sigma \otimes \Omega_0), \tag{3.7}$$

where the parameters u_0, S_0, B_0, Ω_0 are such that the expectation of Σ is equal to the fixed residual covariance matrix of Minnesota prior and the prior expectation and variance of B is that of the Minnesota prior (with $\theta = 1$). The hyperparameter ϕ measures the tightness of the prior: when $\phi = 0$ the prior is imposed exactly and the data do not affect the estimates, while as $\phi \to \infty$ the prior becomes loose and the posterior estimates approach the OLS estimates. For the time being, we set the value of θ to be very small, i.e., we will apply a tight prior, which allows to put a lot of weight on the a priori belief that exchange rates follow a driftless random walk. Apart from that, as the number of variables in the VAR increases, the tighter the prior should be in order to avoid overfitting. The conditional posterior distributions are also of the Normal-Inverted Wishart form:

$$\Sigma \sim IW(\bar{u}, \bar{S}); B \mid \Sigma, Y \sim N(\bar{B}, \Sigma \otimes \bar{\Omega}), \tag{3.8}$$

where the bar denotes that parameters are those of the posterior distribution. As it was shown by Zellner [106] we can obtain the marginal posterior distribution of B, by intergrating out Σ which will generate a multivariate t: $B \mid Y \sim MT(\bar{\Omega}{-}1, \bar{S}, \bar{B}, \bar{u})$.

To derive the posterior distributions, it is necessary to rewrite the VAR in the form of a multivariate regression model. Let's define $B = (\Phi_{0,h}, \Phi_{1,h})\prime$ and $X_t = (1, Y_{t-h})\prime$, then Equation 3.6 can be written as:

$$Y_t = B'X_t + e_t \tag{3.9}$$

and rewriting Equation 3.9 in data-matrix notation yields:

$$Y = XB + E. \tag{3.10}$$

In Equation 3.10 the observations are by row and equations by column, so that $Y = (Y_1, \ldots, Y_T)'$ is a TxN matrix of dependent variables and $X = (X_1, \ldots, X_T)'$ is a TxN matrix of explanatory variables. The matrix $E = (e_1, \ldots, e_T)'$ is the matrix of disturbances, where the generic column is $\epsilon_i \sim IIDN(0, \Psi \otimes I)$.

The selected prior can alternatively be implemented in the form of dummy variable observations. More specifically, the addition of T_d dummy observations Y_d and X_d to the system is equivalent to impose this prior with $\Omega_0 = (X_d' X_d)^{-1}$, $\Psi_0 = (Y_d - X_d B_0)'(Y_d - X_d B_0)$, $B_0 = (X_d' X_d)^{-1} X_d' Y_d$ and $a_0 = T_d - M - N - 1$. The conditional posterior distributions are also of the Normal Inverted Wishart form:

$$B \mid \Psi, Y \sim N(\bar{B}, \Psi \otimes \bar{\Omega}), \quad \Psi \mid Y \sim IW(\bar{\Psi}, \bar{a}), \tag{3.11}$$

where the bar denotes that the parameters are taken from the posterior distribution. We can obtain the marginal posterior distribution of B, by integrating out Ψ and we will get a multivariate t: $B \mid Y \sim MT(\bar{\Omega}^{-1}, \bar{\Psi}, \bar{B}, \bar{a})$. Given the prior parameters $\Omega_0, \Psi_0, B_0, a_0$ and defining $\hat{B}$ and $\hat{E}$ as the traditional OLS estimates, the posterior parameters are given by $\bar{\Omega} = (\Omega_0^{-1} + X'X)^{-1}$, $\bar{\Psi} = \hat{B}'X'X\hat{B} + B_0'\Omega_0^{-1}B_0 + \Psi_0 + \hat{E}'\hat{E} - \hat{B}'\bar{\Omega}^{-1}\hat{B}$, $\bar{B} = \Omega(\Omega^{-1}B_0)\bar{} + X'X\bar{B})$ and $\bar{a} = T + a_0$ [1].

If the prior is specified in the form of dummy observations, the posterior can be computed with a simple OLS regression, after augmenting the model in 3.10 with the dummy variables. The augmented model has the following form:

$$Y_* = X_* B_* + E_*, \tag{3.12}$$

the posterior parameters are given by $\bar{\Omega} = (X_*' X_*)^{-1}$, and $\bar{B} = (X_*' X_*)^{-1} X_*' Y_*$. [1]

[1] A complete derivation can be found in Zellner [106]
[1] As derived in Kadiyala and Carlson [69].

3.3 Results

In the subsequent section we describe the data and the forecasting exercise, followed by an analysis of the empirical results of the forecast evaluation.

3.3.1 Data-Forecasting Exercise

The data used in the paper are the monthly averages of the exchange rates against the US Dollar for 24 currencies taken from the OECD Database. As it is reported in Table 3.1, Augmented Dickey Fuller (ADF) test to include both a constant and a time trend in the equation, was performed in order to detect the presence of a unit root in the exchange rates series. As it is obvious from the results, the null hypothesis of the presence of a unit root cannot be rejected for most of the currencies at the 1% significance level, as a result the series are transformed by taking logarithms of the levels, so that the transformed series are stationary (see results of the ADF test for the first differences).

The forecasting exercise is performed in pseudo real time using a rolling estimation window of 10 years (120 months) and the models are projected forward up to 12 months ahead. The initial estimation window is 1990:01-1999:12 and on the basis of such estimates, forecasts up to 12-step ahead (i.e for the period 2000:01-2000:12) are produced and stored. Then the estimation window moves forward one month, i.e. 1990:2-2000:01, and new forecasts are produced for the 2000:02-2001:01 period and so on. The results will be evaluated in terms of Mean Forecast Error (MFE) generated by model M when forecasting the exchange rate (against the US Dollar) of currency i at horizon h. Defining $\hat{y}^M_{i,t+h|t}$ as the $h-$step ahead forecast, the error at time t is:

$$FE^M_{h,t} = \hat{y}^M_{i,t+h|t} - y_{i,t+h} \tag{3.13}$$

and the $h-$ step ahead MFE is defined as:

$$MSE^M_{i,h} = \frac{1}{T}\sum_{t=1}^{T}(FE^M_{h,t}) \tag{3.14}$$

where T is the total number of computed forecasts.

In the same way, the Mean Absolute Forecast Error (MAFE) is defined in the following way:

$$MAFE^M_{i,h} = \frac{1}{T}\sum_{t=1}^{T} \mid FE^M_{h,t} \mid \tag{3.15}$$

this measure can produce useful results for the forecast exercise since it assigns smaller weight to larger forecast errors than the MFE. The benchmark model is a driftless random walk, which produces the following $h-$step ahead forecast of the exchange rate:

$$\hat{y}_{i,t+h} = y_{i,t} \tag{3.16}$$

Finally, the last forecasting evaluation criterion examined is the U-Theil statistics, which will take the value 1 under the naïve forecasting method. Values less than 1 indicate greater forecasting accuracy of the Model M than the naïve forecasting method, values greater than 1 indicate the opposite.

$$U_2 = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T-1}\frac{(\hat{y}_{i,t+1}-y_{i,t+1})^2}{y_{i,t}}}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T-1}\frac{(y_{i,t+1}-y_{i,t})^2}{y_{i,t}}}} \tag{3.17}$$

For the specific models under consideration, the forecasting equations have the following form:

$$\hat{y}_{t+h} = \hat{\beta}_F F_t + \hat{\beta}_w w_t \tag{3.18}$$

where F_t are the first r principal components of the exchange rates at time t as it was defined in section 3.2.1. If the number of the extracted r using the Kaiser - Guttman criterion, as explained above, is smaller than the cross sectional dimension, then the explanatory parameters of the model will be reduced, which might lead to potential gains in out-of sample forecasting accuracy. In the BVAR specification, the vector of exchange rates $Y_t = (y_{1,t}, y_{2,t}, \ldots, y_{N,t})\prime$ at time $t+h$ is:

$$\hat{Y}_{t+h} = \hat{\Phi}_{0,h} + \hat{\Phi}_{1,h} Y_t \tag{3.19}$$

where $\hat{\Phi}_{0,h}$ and $\hat{\Phi}_{1,h}$ are the posterior means of the matrices coefficients in Equation 3.15. In the comparison exercise, a simple autoregressive model is also included; the optimal lag length L* is chosen according to the Bayesian Information Criterion (BIC) and the reported results of the exchange rates forecasts based on the AR(L*) are obtained in the following way:

$$\hat{y}_{i,t+h} = \hat{\alpha}_{i,h} + \hat{\beta}_{i,h}(L^*)\hat{y}_{i,t} \tag{3.20}$$

where $\hat{\alpha}_{i,h}$ and $\hat{\beta}_{i,h}(L^*)$ are the coefficients from the regression of $y_{i,t}$ on its own past lags.

3.3.2 Results

Starting from the Principal Components analysis, the total variance explained by the initial eigenvalues is considered. The factor model under examination suggests retaining 4 factors, as the eigenvalues for the first 4 components are 12.71, 6.33, 1.70 and 1.26 respectively and according to the Kaiser - Guttman criterion the retained factors are those with an eigenvalue larger than 1. A very interesting pattern emerges with regard to the loading factors; the loading factors on the first common component are all positive (except for one) for all countries. This can be interpreted as an indication that all currencies move in the same direction in response to movements in the first common factor, i.e. the US Dollar appreciates or depreciates against all currencies simultaneously. Since the panel consists of bilateral exchange rates against the US Dollar, the first factor is not driven by idiosyncratic shocks in any of the individual countries in the panel-except for the United States.

In terms of the forecasting exercise, in order to facilitate the comparison of the models, results are provided in terms of Theil U statistics of a given model against the driftless naive random walk model:

$$U_2 = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T-1}\frac{(FE_{i,t+1})^2}{y_i,t}}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T-1}\frac{(y_{i,t+1}-y_{i,t})^2}{y_i,t}}} \tag{3.21}$$

A value of U_2 below 1 denotes that the model under consideration outperforms the RW in the out-of-sample forecasting accuracy. The results of the forecasting exercise are summarised in Tables 3.4 - 3.5 for respectively the factor model and BVAR each one against the random walk. Each column in the tables refers to a different exchange rate of currency i against the US Dollar and each row to a different forecast horizon, ranging from 1 to 12.

The main result from Tables 3.4-3.5 is that, as it was already confirmed by the previous empirical literature, beating the naive random especially for the 1-step ahead forecasting horizon is challenging. However, when compared the two multivariate time series models under examination, i.e the BVAR and the factor model, it seems that the Factor Model produces fairly good forecasts. In particular, for those currencies for which the factor model outperforms the random walk, where the U-Theil statistics is below 1, the average gains for all the forecast horizons range from 1 to 3%. The pattern of the gains, in the majority of the cases, has a U-shape, namely there are gains around 1% at very short and very long forecast horizons, and larger gains at intermediate forecast horizons.

A more disaggregate investigation reveals that the factor model specification outperforms the random walk for most currencies and forecast horizons. In particular, for h = 1 the factor model outperforms the random walk in only 3 cases out of 24, however for h=3 and h=6 the factor model is better in 12 cases out of 24, and in 14 cases for h = 12. It is also interesting to focus on the forecasting performance for some prominent currencies, such as the euro, the GB Pound, and the Japanese Yen. For the Euro-Dollar and the GBP-Dollar exchange rates, the factor model outperforms the random walk at all horizons, generating a value for the U Theil statistics lower than 1. For example, for h=12, the gain in forecasting accuracy in the Euro-Dollar exchange rate is 2.2%, 3.6% for the GBP-Dollar exchange rate respectively. For the Yen-Dollar rate the evidence is more mixed, as the naive random walk seems to outperform, although the BVAR provides us with better forecasts at longer horizons, but the gains are smaller when compared to the factor model specification. For two major trading partners of the US, Canada and Mexico, the BVAR performs very well for the former country, with gains ranging from 1% for h = 1 to 9% for h = 12, and only slightly worse for the latter country at short horizons, with losses smaller than 4% and gains of about 2.5% for h = 5.

Finally, the stars in the tables 3.6 - 3.7 denote rejection of the null of equal forecast accuracy of the models at 1%, 5%, and 10%, according to the Giacomini and White [59] statistic. This is a test of equal forecasting method accuracy and as such can handle forecasts based on both nested and non-nested models, regardless of the estimation procedures used in the derivation of the forecasts, including Bayesian methods. As it becomes clear from Tables 3.6 and 3.7 although the RMSFE across currencies is below 1 in several instances, only in a few cases the differences in the forecasts are statistically significant.

Last but not least, an interesting pattern arises from the forecasting results of the Factor Model, if we split the results into 'developed' and 'emerging' currencies, as it is reported in Tables 3.4 - 3.5. While the currencies of the developed economies do systematically better against the random walk specification and the statistical gains are larger on average, the evidence is more mixed when it comes to the currencies of the emerging economies (although Factor Model remains a better forecasting model compared to the BVAR, AR(L*) and unrestricted VAR specifications). Especially, for some currencies, like the Indonesian Rupiah and the Russian Ruble, the results were not that encouraging. A potential explanation of this finding might be that the nature of the cross sectional information picked up by the model is explored in more details when assessing the cross sectional dependence among the different groups of currencies.

3.3.3 Trading Strategies

The forecasting results based on the multivariate time series models using statistical measures reported above are raising some interesting points for the statistical ability of pure time series models for exchange rate forecasting. However, they indicate little about the ability of this approach to generate persistent profits in an investment portfolio context.

As a consequence, we now turn our attention to the economic evaluation of these multivariate time series models under examination, hence the economic gains obtained by using a trading strategy based on the BVAR and FM forecasts. This exercise is mainly inspired by Sager and Taylor [90] where the authors assess whether the Clarida -Taylor framework can be used to generate significant trading profits in combination with an acceptable degree of risk in a realistic investment portfolio context.

The basic intuition behind this strand of literature is that the generated forecasts are used to implement trading positions within a simulated investment portfolio that incorporates realistic assumptions on transaction costs and position limits. In a second step, they assess the investment performance of associated trading rules in terms of their ability to generate returns in excess of a strategic benchmark return, rather than in terms of the average size of associated forecast errors.

However, here a simpler version of the trading strategy is employed and is applied in the following way; The investor owns a capital in US dollars, and at each point in time takes the decision on whether to invest it in a foreign currency or not. The investment decision is based on the prediction made by the time series models considered here. In this exercise, both the BVAR and FM are being assessed based on their forecast about the future path of the exchange rates. More specifically, if the model predicts the foreign currency will appreciate, then the investor will go short in US Dollars and long in the foreign currency, whereas if the model predicts a depreciation the investor will hold his position and stay long in dollars. A very important assumption here is that at each point in time the investor realises the gain/loss and reinvests the initial capital, based on the realisation.

Table 3.8 displays the results of this simple trading strategy for the BVAR, the Factor Model and the AR(L*) model specifications. For each of the three panels in the table the first column displays the average return, the second the standard deviation, and the third the Sharpe Ratio, which is a rather straightforward way of assessing the mean-variance trade-off. It is well defined in the Finance literature as the average return earned in excess of the risk-free rate per unit of volatility or total risk. Subtracting the risk-free rate from the mean return, the performance associated with risk-taking activities can be isolated.

$$S(x) = \frac{(r_x - R_f)}{\sigma(x)} \tag{3.22}$$

where x is the initial investment, r_x is the average rate of return of x, R_f is the risk-free rate of return and $\sigma(x)$ is the standard deviation of the excess return. As it is indicated by the Table 3.8 with the results of the performance of trading strategies, overall the strategy based on the dynamic factor model specification provides positive returns. Moreover, the factor model strategy performs better than the one based on the AR(L*) in terms of both returns and standard deviation, as shown by the Sharpe Ratios, which are higher in 14 cases out of 24 and when comparing the Factor Model specification with the BVAR in terms of Sharpe ratios, then the Factor Model specification generates higher ratios in 16 out of 24 cases under consideration. Finally, it is worth mentioning that the trading strategy based on the Factor Model forecasts, involved systematically fewer transactions with respect to the AR specification, implying that the Factor Model induces the investor to change his position less often, which means that the transaction costs associated with such strategy would be smaller. The reason why this is the case is that the Factor Model predicts fewer changes between appreciation and depreciation of the foreign currency, hence fewer changes in trading positions and lower transaction costs.

3.4 Conclusions

Over the two decades since the publication of the landmark papers of Meese and Rogoff [87] [86], little robust evidence has emerged to challenge their devastating finding that fundamentals-based exchange rate models cannot outperform naive random walk models in terms of out-of-sample forecast accuracy. Having a forecasting model which is both consistent with economic theory and forecasts well is very appealing, but the simple task of forecasting is significant in his own rights.

In this paper, the issue of forecasting a large set of exchange rates using multivariate time series models was addressed. In particular, two alternative forecasting models, a Factor Model and a Bayesian VAR Model, have been examined in terms of their ability to generate accurate predictions of the future path of the exchange rates and to beat the most challenging benchmark model, the naïve random walk, taking into account information from the large panel of exchange rates, when needed.

The forecasts of the Factor Model that were generated through a two-step procedure, whereby the factors are first extracted as principal components and then taken as given for the estimation of the parameters of the model, appear to outperform the naïve random walk for some of the developed economies' currencies at longer forecasting horizons.

The results of the Bayesian VAR model, in which exchange rates a-priori follow a random walk without drift have also provided mixed evidence, although this specification appears to fit better at $h = 1$ and especially when compared to the unrestricted version of the VAR specification. These results confirm that the shrinkage parameter approach (namely the BVAR) plays a significant role in summarising the information contained in large datasets.

We applied the proposed models to forecast a panel of 24 exchange rates vis-a-vis the US Dollar, finding that it can lead to gains in forecast accuracy for the large majority of the exchange rates under consideration. The gains arise at all forecast horizons, including the very short ones where the random walk forecast is typically extremely hard to outperform. The forecast gains are typically in the range of 1- 3%, but in some relevant cases, such as the Euro-Dollar and the GBP-Dollar, they can go up to 6-9%. Moreover, a simple trading strategy based on the BVAR and FM forecasts provides positive returns, higher than those from the simple AR forecasts.

Finally, the relatively good performance of the models appear to be related more to the intermittent use of information in the large panel than to changes in the persistence of the exchange rates. In addition, in the post 2000 period the information in the exchange rates of emerging countries seems to matter for forecasting those of the developed countries more than vice versa, a finding that deserves additional research.

Augmented Dickey Fuller Test for the full sample size

	Log Level	**First Differences**
AUST	-1.498	-11.077^{*}
BRA	-3.506^{*}	-5.164^{*}
CANA	-0.730	-11.829^{*}
CHIL	-2.350	-10.345^{*}
CHIN	-2.519	-15.281^{*}
CZE	-0.971	-11.540^{*}
EURO	-1.697	-10.575^{*}
GBP	-2.742	-11.358^{*}
HUNG	-1.350	-14.841^{*}
INDI	-3.943^{*}	-13.164^{*}
INDO	-1.432	-12.163^{*}
ICEL	-1.410	-10.294^{*}
ISRA	-2.771	-11.479^{*}
JAPA	-2.090	-11.803^{*}
MEXI	-1.739	-12.064^{*}
NEWZ	-1.607	-10.920^{*}
NORW	-2.280	-10.540^{*}
POLI	-1.808	-8.606^{*}
RUS	-2.047	-15.657^{*}
SAFR	-1.746	-11.516^{*}
SKOR	-1.928	-11.803^{*}
SWED	-2.464	-9.839^{*}
SWIS	-1.375	-12.094^{*}
TURK	-3.449	-9.764^{*}

TABLE 3.1: * Denotes rejection of the null of a unit root at 1% level

Countries	**Comp1**	**Comp2**	**Comp3**	**Comp4**
AUST	.543	.784	.055	.021
BRA	.834	-.307	-.286	-.329
CANA	.462	.767	-.146	-.290
CHIL	.909	-.162	.058	.030
CHIN	.740	-.025	-.224	-.591
CZEC	.177	.943	.046	-.175
EURO	.547	.806	.062	.027
GBP	.341	.564	-.629	.307
HUNG	.877	-.055	.258	.035
INDI	.916	-.294	-.116	-.069
INDO	.852	-.350	.274	.130
ICEL	.626	-.212	-.352	.624
ISRA	.924	-.231	.060	-.196
JAPA	-.247	.529	.724	-.017
MEXI	.832	-.501	.065	-.058
NEWZ	.317	.849	.053	.291
NORW	.564	.798	-.038	.036
POLI	.862	.032	.107	-.125
RUS	.622	-.330	.471	.226
SAFR	.913	-.299	.094	.145
SKOR	.887	-.066	.088	.210
SWED	.838	.452	.-176	.056
SWIS	.165	.933	.209	-.022
TURK	.885	-.443	.077	-.036

TABLE 3.2: Extraction Method-**Principal Components Analysis**

	Initial Eigenvalues			Sums of Squared Loadings		
Component	Total	% Variance	Cumulative %	Total	%Variance	Cumulative %
1	12.711	52.964	52.964	12.711	52.964	52.964
2	6.330	26.377	79.341	6.330	26.377	79.341
3	1.709	7.121	86.462	1.709	7.121	86.462
4	1.261	5.255	91.717	1.261	5.255	91.717

TABLE 3.3: Total Variance Explained-**Principal Components Analysis**

Developed Countries					
Forecasting Horizon	AUST	CANA	ICEL	JAPA	NEWZ
1	1.019	1.227	1.205	1.294	1.379
2	1.002	1.121	1.185	1.159	1.324
3	0.987	0.998	1.194	1.168	1.315
4	0.966	0.986	1.091	1.159	1.310
5	0.902	0.988	0.994	1.141	1.284
6	0.959	0.960	0.985	1.135	1.265
7	0.923	0.959	0.991	1.117	1.234
8	0.917	0.956	0.983	1.121	1.225
9	0.901	0.966	0.985	1.113	1.221
10	0.884	0.978	0.982	1.122	1.219
11	0.890	0.991	0.978	1.054	1.112
12	0.824	0.996	0.972	1.046	1.111
	NORW	SWED	SWIS	GBP	EURO
1	1.093	0.992	1.005	0.996	1.010
2	1.091	0.989	1.004	0.988	0.991
3	1.079	0.972	0.998	0.979	0.994
4	1.060	0.986	0.981	0.963	0.985
5	1.054	0.945	0.983	0.942	0.973
6	1.041	0.958	0.989	0.933	0.964
7	1.028	0.932	0.978	0.928	0.952
8	1.011	0.952	0.969	0.925	0.948
9	1.009	0.910	0.959	0.938	0.931
10	0.993	0.908	0.943	0.948	0.945
11	0.988	0.905	0.978	0.955	0.966
12	0.984	0.899	0.971	0.964	0.978
Emerging Economies					
	CHIL	CZEC	HUNG	ISRA	SKOR
1	1.060	0.999	1.166	1.147	1.197
2	1.054	0.992	1.033	1.132	1.141
3	1.048	0.974	1.038	1.128	1.159
4	1.089	0.968	0.997	1.119	1.184
5	1.094	0.940	0.945	1.112	1.117
6	1.079	0.932	0.929	1.116	1.104
7	1.071	0.928	0.913	1.104	1.105
8	1.068	0.921	0.911	1.102	1.100
9	1.062	0.918	0.909	1.095	1.098
10	1.058	0.915	0.905	1.091	1.094
11	1.044	0.911	0.901	1.085	1.091
12	1.041	0.908	0.904	1.078	1.087
	MEXI	POLI	TURK	BRA	CHIN
1	1.342	1.410	1.128	1.213	7.832
2	1.218	1.180	1.009	1.278	7.143
3	1.172	1.218	0.994	1.289	6.608
4	1.125	0.981	1.015	1.281	6.218
5	1.063	0.905	0.943	1.264	5.644
6	1.069	0.963	0.989	1.153	5.079
7	1.054	0.941	1.008	1.103	3.854
8	1.049	0.896	0.978	1.139	3.501
9	1.117	0.899	0.931	1.217	3.223
10	1.113	0.836	0.903	1.212	2.861
11	1.029	0.871	0.887	1.160	2.980
12	1.019	0.878	0.846	1.174	2.735
	INDI	INDO	RUS	SAFR	
1	1.046	1.464	12.514	0.898	
2	0.924	1.413	9.540	0.807	
3	0.904	1.378	8.797	0.812	
4	0.968	1.372	8.285	0.820	
5	1.096	1.413	8.515	0.793	
6	1.049	1.376	8.032	0.740	
7	0.930	1.427	7.444	0.805	
8	0.907	1.339	6.148	0.844	
9	0.937	1.337	5.869	0.827	
10	0.965	1.286	5.377	0.786	
11	0.862	1.194	4.615	0.814	
12	0.895	1.119	4.617	0.788	

TABLE 3.4: U-Theil Statistics for **Factor Model** Specification

Developed Countries					
Forecasting Horizon	AUST	CANA	ICEL	JAPA	NEWZ
1	1.182	0.997	1.084	1.068	1.005
2	1.135	0.991	1.003	1.057	1.002
3	1.131	0.982	1.013	1.044	1.011
4	1.129	0.952	1.021	1.037	1.009
5	1.110	0.949	1.011	1.032	1.005
6	1.102	0.933	1.009	1.029	1.004
7	1.087	0.921	1.015	1.022	1.001
8	1.070	0.919	1.024	1.019	0.991
9	1.053	0.917	1.030	1.011	0.983
10	1.033	0.911	1.035	1.008	0.987
11	1.022	0.909	1.039	1.002	0.983
12	1.013	0.901	1.040	1.039	0.984
	NORW	SWED	SWIS	GBP	EURO
1	1.065	1.009	1.110	1.192	0.994
2	1.004	0.998	1.047	1.184	0.993
3	1.021	1.000	1.070	1.981	0.992
4	1.032	0.995	1.090	1.917	0.991
5	1.040	0.999	1.078	1.932	0.983
6	1.044	1.003	1.042	1.837	0.971
7	1.047	1.003	1.031	1.739	0.974
8	1.049	0.997	1.021	1.638	0.969
9	1.052	0.996	1.045	1.536	0.961
10	1.055	0.993	1.050	1.436	0.958
11	1.058	0.987	1.036	1.233	0.942
12	1.063	0.985	1.045	1.030	0.938
Emerging Economies					
	CHIL	CZEC	HUNG	ISRA	SKOR
1	1.997	1.066	1.025	1.053	0.997
2	1.989	1.042	1.014	1.037	0.985
3	1.982	1.050	1.016	1.048	0.996
4	1.976	1.069	1.014	1.048	0.998
5	1.969	1.091	1.010	1.045	0.995
6	1.826	1.012	1.045	1.040	0.991
7	1.884	1.036	1.005	1.036	0.988
8	1.835	1.055	1.002	1.030	0.982
9	1.821	1.074	0.992	1.024	0.975
10	1.647	1.063	0.982	1.021	0.969
11	1.553	1.058	0.969	1.021	0.964
12	1.552	1.019	0.955	1.022	0.959
	MEXI	POLI	TURK	BRAZ	CHIN
1	0.998	1.001	0.975	1.133	1.490
2	0.991	1.010	1.017	1.081	1.558
3	0.989	1.011	1.036	1.075	1.580
4	0.983	1.010	1.050	1.047	1.583
5	0.975	1.004	1.064	1.085	1.579
6	0.981	0.992	1.074	1.039	1.572
7	0.978	0.983	1.082	1.087	1.563
8	0.986	0.976	1.092	1.223	1.051
9	0.991	0.969	1.103	1.045	1.538
10	1.004	0.960	1.113	1.063	1.524
11	1.008	0.949	1.124	1.078	1.510
12	1.014	0.937	1.134	1.081	1.496
	INDI	INDO	RUS	SAFR	
1	0.996	1.197	3.126	1.985	
2	0.991	1.169	1.417	1.925	
3	0.990	1.098	1.978	1.953	
4	0.987	1.120	2.193	1.978	
5	0.983	1.128	2.371	1.200	
6	0.979	1.124	2.575	1.224	
7	0.973	1.120	2.793	1.138	
8	0.965	1.120	2.949	1.145	
9	0.954	1.124	3.088	1.152	
10	0.943	1.124	3.089	1.161	
11	0.933	1.144	3.254	1.172	
12	0.924	1.153	3.398	1.185	

Table 3.5: U-Theil Statistics for **BVAR Model**

RMSFE of Factor Model against Random Walk

Horizon	1	2	3	4	5	6	7	8	9	10	11	12
Currencies												
AUST	1.219	1.204	1.193	1.184	1.173	1.165	1.121	1.123	1.111	1.109	1.102	1.098
BRA	1.992	1.821	1.671	1.531	1.215	1.182	1.167	1.541	1.324	1.231	1.198	1.187
CANA	0.996	0.992	0.991	0.981	0.984	0.991	0.997	1.004	1.015*	0.992	0.991	0.987
CHIL	1.331	1.228	1.221	1.129	1.117	1.109	1.094	1.083	1.072*	1.062	1.054	1.051
CHIN	5.851	3.221	2.734	2.643	2.444	2.212	1.982	1.987	1.977	1.909	1.112	1.104
CZEC	4.241	4.328	4.821	4.339	3.481	3.213	3.674	3.505	3.434	3.149	2.986	2.891
EURO	1.119	1.108	1.096	1.082	1.073*	1.187	1.201	1.219	1.189	1.174	1.165	1.132
GBPP	1.233	1.219	1.204	1.195	1.187	1.164	1.158	1.152	1.139	1.124	1.119	1.111
HUNG	1.931	1.543	1.488	1.452	1.443	1.432	1.411	1.387	1.376	1.365	1.358	1.287
INDI	6.612	4.381	3.974	3.851	3.788	3.289	3.118	2.895	2.542	2.122	1.998	1.987
INDO	8.334	6.831	5.322	5.124	4.981	4.512	3.821	3.281	2.848	2.193	2.359	2.294
ICEL	1.102	1.094	1.091	1.084	1.081	1.077	1.069	1.058	1.043	1.039	1.028	1.019*
ISRA	1.739	1.722	1.699	1.671	1.689	1.695	1.689	1.603	1.588	1.571	1.555	1.490
JAPA	1.903	1.888	1.852	1.838	1.826	1.812	1.806	1.794	1.687	1.513	1.435	1.292
MEXI	1.009	0.996	0.988**	0.981**	0.978	0.989	0.990***	0.981	0.979	0.982	0.963	0.961
NEWZ	1.368	1.329	1.312	1.308	1.296	1.283	1.274	1.263	1.254	1.241	1.239	1.228
NORW	2.123	2.118	2.113	2.109	2.094	2.091	2.084	2.072	2.066	2.058	2.041	2.037
POLI	2.289	2.198	2.176	2.169	2.159	2.143	2.129	2.398	2.409	2.415	2.387	2.356
RUS	3.178	3.298	3.176	2.873	2.692	2.513	2.498	2.381	2.273	2.189	2.154	2.091
SAFR	3.247	3.123	3.076	2.876	2.634	2.474	2.129	2.091	1.982	1.763	1.678	1.562
SKOR	1.987	1.942	1.895	1.748	1.634	1.592	1.433	1.325	1.263	1.191	1.187	1.172
SWED	1.008	1.006	0.998**	1.019**	1.028	1.031	1.029	1.012*	1.009	1.007	1.002	0.997
SWIS	1.163	1.158	1.149	1.122	1.118	1.109	1.098	1.087	1.081	1.076	1.062	1.058*
TURK	2.361	2.132	2.098	1.994	1.982	1.962	1.943	1.938	1.929	1.915	1.892	1.888

TABLE 3.6: The symbols ***,**,*, denote rejection of the null of equal forecast accuracy at 1%,5%, and 10%, according to the Giacomini and White (2006)test.

RMSFE of BVAR against Random Walk

Horizon	1	2	3	4	5	6	7	8	9	10	11	12
Currencies												
AUST	1.122	1.102	1.099	1.082	1.071	1.062	1.031	1.029	1.011	1.009	1.002	0.992
BRA	2.001	1.195	1.189	1.125	1.196	1.185	1.114	1.044	1.021	0.992	0.989	0.931
CANA	0.984	0.991	0.973^{*}	0.963	0.951	0.943	0.917	0.893	0.873	0.856	0.837	0.831
CHIL	1.827	1.226	1.273	1.234	1.144	1.012	0.997^{**}	0.987	0.908	0.897	0.888	0.881
CHIN	3.824	2.261	1.735	1.346	1.144	1.012^{*}	0.987	0.987	0.977	0.908	0.991	0.801
CZEC	2.578	2.278	2.265	2.357	2.442	2.523	2.674	2.705	2.834	2.843	2.836	2.850
EURO	1.055	0.952	0.979	1.067	1.117	1.285	1.353	1.389	1.401	1.438	1.449	1.488
GBPP	1.958	1.406	1.367	1.239	1.152	1.131	1.119	1.152	1.220	1.229	1.265	1.309
HUNG	2.994	2.393	2.381	2.524	2.641	2.743	2.875	3.050	3.311	3.465	3.599	3.669
INDI	2.508	1.316	0.974	0.822^{**}	0.788^{**}	0.789^{***}	0.837	0.895	0.928	0.922	0.998	1.119
INDO	7.531	3.899	3.022	2.595	2.517	2.516	2.415	2.203	1.888	1.572	1.355	1.290
ICEL	1.252	0.902	0.877	0.994	1.053	1.108	1.224	1.423	1.698	1.886	2.072	2.175
ISRA	1.899	1.302	1.259	1.251	1.189	1.125	1.189	1.203	1.888	1.572	1.355	1.290
JAPA	2.903	2.109	1.302	1.638	1.456	1.726	1.734	1.594	1.687	1.814	1.713	1.252
MEXI	1.104	1.284	1.545	1.354	1.418	1.628	1.808	1.933	1.877	1.646	1.547	1.485
NEWZ	1.957	1.328	1.038	0.965	0.966	0.955	0.913	1.002	1.194	1.183	1.205	1.234
NORW	2.037	1.849	1.853	1.845	1.935	2.029	2.248	2.415	2.489	2.522	2.474	2.423
POLI	5.128	3.618	3.281	3.491	3.431	3.361	3.271	3.061	3.085	3.033	3.145	2.990
RUS	5.078	2.991	2.538	2.245	2.017	1.815	1.651	1.523	1.431	1.357	1.298	1.219
SAFR	7.547	4.480	5.015	4.470	3.823	3.471	3.320	3.316	3.327	3.274	3.415	3.461
SKOR	2.174	2.040	2.195	2.381	2.418	2.460	2.513	2.525	2.663	2.651	2.663	2.642
SWED	1.777	1.378	1.331	1.365	1.345	1.344	1.415	1.530	1.629	1.758	1.834	1.887
SWIS	1.278	1.126	1.178	1.259	1.546	1.753	2.025	2.348	2.667	2.725	2.770	2.864
TURK	1.466	1.332	1.313	1.362	1.464	1.556	1.579	1.598	1.743	1.934	2.302	2.674

TABLE 3.7: The symbols ***,**,*, denote rejection of the null of equal forecast accuracy at 1%,5%, and 10%, according to the Giacomini and White (2006)test.

	BVAR			DFM			AR		
	AvgReturn	σ	*SR*	*AvgReturn*	σ	*SR*	*AvgReturn*	σ	*SR*
Currencies									
AUST	0.1894	1.948	0.0972	0.1936	2.019	0.096	0.039	2.0411	0.0191
BRA	0.0641	1.2958	0.0495	0.0892	1.3491	0.0661	0.1532	1.9281	0.0794
CANA	0.2819	1.6128	0.1747	0.2912	1.6912	0.1721	0.1481	1.9381	0.0764
CHIL	0.0318	1.1829	0.0268	0.0419	1.2019	0.0349	0.7912	1.2918	0.6124
CHIN	0.0458	1.2913	0.0354	0.0718	1.3812	0.0520	0.0294	1.4923	0.0197
CZEC	0.5918	2.8910	0.2047	0.4918	2.6817	0.1833	0.4198	2.1981	0.1909
EURO	0.2198	2.8819	0.0762	0.2281	2.1876	0.1042	0.1928	2.1176	0.0910
GBPP	0.1623	1.8361	0.0883	0.1864	1.9182	0.0971	0.0019	1.8081	0.0010
HUNG	0.0671	2.4716	0.0271	0.0719	2.3812	0.0302	0.0291	2.6712	0.0109
INDI	0.0778	0.9871	0.0788	0.0671	0.5817	0.1153	0.0378	0.2189	0.1726
INDO	0.0671	0.9182	0.0730	0.05618	0.4672	0.1201	0.0417	0.2881	0.1447
ICEL	0.0716	0.9182	0.0780	0.0871	1.0928	0.0797	0.0517	1.0821	0.0477
ISRA	0.0823	0.3162	0.2602	0.0582	0.8717	0.0667	-0.0192	1.4092	-0.0136
JAPA	-0.0124	1.7621	-0.0070	-0.0293	1.8977	-0.0154	0.2716	1.8711	0.1451
MEXI	0	0	0	0	0	0	-0.1205	1.4918	-0.0080
NEWZ	0.3001	2.3491	0.1277	0.3202	2.298	0.1393	0.2136	2.1981	0.0971
NORW	0.2819	2.5817	0.1091	0.2918	2.4516	0.1190	0.1284	1.7891	0.0717
POLI	0.2890	2.1099	0.1370	0.2618	1.9827	0.1320	0.1982	1.5618	0.1269
RUS	0.0581	1.7629	0.0329	0.0713	1.8721	0.0380	0.0321	1.4126	0.0227
SAFR	0	0	0	0	0	0	-0.0682	0.7247	-0.0941
SKOR	-0.0305	0.6105	-0.0499	-0.0289	0.9718	-0.0297	0.0486	0.9872	0.0492
SWED	0.0725	2.2674	0.0319	0.0871	2.1982	0.0396	-0.0854	1.7451	-0.0489
SWIS	0.186	2.2781	0.0816	0.1982	2.1872	0.0906	0.1481	2.2091	0.0670
TURK	0.0531	0.3392	0.1565	0.0761	0.4812	0.1581	0.0291	0.0391	0.7442

TABLE 3.8: Performance of Trading Strategies -BVAR, DFM, AR against the random walk

	NAME	CODE
1	AUSTRALIAN Dollar to US Dollar - Exchange Rate	AUST
2	BRAZILIAN Real to US Dollar- Exchange Rate	BRAZ
3	CANADIAN Dollar to US Dollar - Exchange Rate	CANA
4	CHILEAN Peso to US Dollar- Exchange Rate	CHIL
5	CHINESE Yuan to US Dollar - Exchange Rate	CHIN
6	CZECH Koruna to US Dollar - Exchange Rate	CZEC
7	EURO to US Dollar - Exchange Rate	EURO
8	UK to US Dollar -Exchange Rate	GBP
9	HUNGARIAN Forint to US Dollar -Exchange Rate	HUNG
10	INDIAN Rupee to US Dollar -Exchange Rate	INDI
11	INDONESIAN Rupiah to US Dollar-Exchange Rate	INDO
12	ICELANDIC Krona to US Dollar - Exchange Rate	ICEL
13	ISRAELI Shekel to US Dollar - Exchange Rate	ISRA
14	JAPANESE Yen to US Dollar - Exchange Rate	JAPA
15	MEXICAN Peso to US Dollar - Exchange Rate	MEXI
16	NEW ZEALAND to US Dollar -Exchange Rate	NEWZ
17	NORWEGIAN Krone to US Dollar -Exchange Rate	NORW
18	POLISH Zloty to US Dollar- Exchange Rate	POLI
19	RUSSIAN Rubble to US Dollar -Exchange Rate	RUS
20	SOUTH AFRICAN Rand to US Dollar- Exchange Rate	SAFR
21	SOUTH KOREAN Won to US Dollar -Exchange Rate	SKOR
22	SWEDISH Krona to US Dollar- Exchange Rate	SWED
23	SWISS Franc to US Dollar-Exchange Rate	SWIS
24	TURKISH Lira to US Dollar -Exchange Rate	TURK

TABLE 3.9: Data- source: Bank for International Settlements

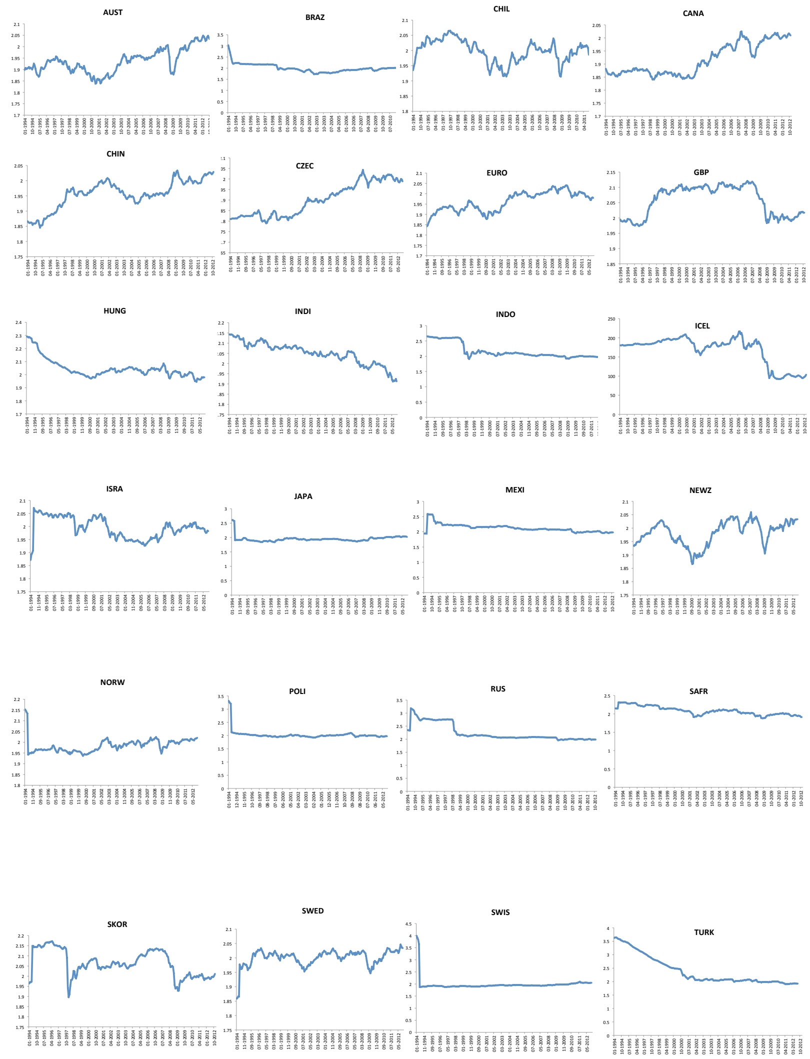


FIGURE 3.1: Monthly Exchange Rate Data (in natural logarithms)

Chapter 4

An index for the Euro Area GDP growth

4.1 Introduction

Due to the recent economic disturbances affecting the world economy, there has been an explosive interest in the early assessment of the short term evolution of economic activity by both the academic community and professional forecasters. The academic literature and the press are full of references to short term GDP growth rate forecasts and its successive revisions which are currently improving with the ongoing economic developments for most of the economies. However, the vast majority of the forecasts released by relevant institutions do not always make explicit the methodology followed to compute their forecasts. Therefore, it is difficult to replicate and intuitively understand the forecasts. In fact, the forecasts of many of these institutions explicitly or implicitly rely on the judgment of experts, which might be helpful in terms of increase the precise of their forecast, but implies two main issues. Firstly, all the forecasts that rely on judgements make the forecasting process a black box which becomes only clear to the mind of the forecaster but not a tool publicly available and easily replicable. The second drawback is that forecasts that rely on judgments of professional forecasters make the forecasting process a subjective exercise that relies on the choice of variables that are included, instead of an objective quantitative and measurable analysis. As a consequence, forecasters may read the news and the announcements of the Central Banks, and be affected by a general business environment that may or may not be accurate to describe the current economic situation. But at the same time, forecasters may even affect the news and therefore, may contribute to create expectations which, if they are not objectively quantifiable, may be only a partial description of the economic situation.

As a consequence, in order to circumvent these problems, in this paper we attempt to set up a model which automatically computes the forecasts when new information becomes available and practically conduct a pseudo-real time analysis. In that sense, the model has the same advantages as the judgmental forecast in terms of the ability to adapt to new information, but it avoids the serious drawbacks of the subjective exercise mentioned before. Regarding the automatic forecasting methods, the most familiar are the standard time series processes developed by Box and Jenkins and their posterior refinements, including multivariate time series process and error correction models. To predict GDP, these models usually rely on quarterly series which are usually published with a delay which ranges from about 45 to 60 days. Therefore, a simple example for illustration would show that, on January 25th 2010, when forecasting next quarter of GDP growth, i.e. the second quarter of 2010, the standard time series models would use data corresponding to the third quarter of 2009. These forecasts, apart from not capturing the abrupt economic changes occurred in the fourth quarter of 2009 and the first month of 2010, will be subject to strong revisions in the reference series that take place subsequently. With this outdated information, the standard autoregressive models usually suffer from strong mean reverting and their forecasts are therefore seriously biased towards the mean which may lead to misleading forecasts, especially in periods of economic turbulences. To account for this problem, it appears like a natural framework to use a dynamic factor model which includes economic indicators that are related to GDP growth but are much promptly available. One potential alternative specification could be based on transfer functions which include the set of indicators as explanatory variables. However, estimating these models can become problematic mainly when the number of indicators increases. For these reasons, dynamic factor models become the most appropriate framework to compute the forecasts. These specifications are based on the assumption that the joint dynamics of GDP growth and the indicators can be decomposed in two components. For each of these series, the first component refers to the common dynamics whereas the second component refers to its idiosyncratic dynamics.

In the recent empirical literature, two alternative dynamic factor models are usually applied. The first one is the factor models that is based on large sets of economic indicators which are estimated with the use of approximate factor models as in Angelini, Camba-Mendez, Giannone, Reichlin and Runstler [3] for Euro-area data and by Camacho and Sancho [91] for Spanish data. The other alternative relies on the previous reasonable pre-screenings of the series which are estimated by using strict factor models and has recently been applied by Camacho and Perez-Quiros [21] and by Frale, Marcellino, Mazzi and Proietti [57] to Euro-area data. Regarding the well documented controversy between using large versus small scale factor models, it has been pointed out by Boivin and Ng [18] that the asymptotic advantages of large-scale factor models are frequently far from holding in empirical applications. In addition, Alvarez-Aranda, Camacho and Perez-Quiros [1] examine the empirical pros and cons of forecasting with large versus small factor models. The main message of this line of research is that, in empirical applications, the larger is the number of time series, the higher is the correlation of the idiosyncratic part, and this correlation might bias the results of the estimated common factor. Therefore, according to these authors, more is not always better from a forecasting point of view. In addition, Bai and Ng [8] have shown the importance of having parsimonious specifications in order to improve the forecasting ability of factor models, even when zero cross-correlation among the idiosyncratic part holds.

Within the spirit of the above mentioned discussion, we propose a small scale factor model to compute short term forecasts of the Euro GDP growth rate. The model is constructed to deal with the typical problems affecting real-time economic releases. First, the model deals with ragged edges in order to take into account all the available information which is released in a non-synchronous way. Second, the model accounts for data with mixed frequencies, in order to bridge monthly indicators with quarterly GDP. Third, the model is a simple algorithm that can be automatically updated, so the model handles potential economic instabilities, because, if the predictive power of any variable diminishes during the course of some periods, the variable will reduce its weight and its loading factor. Finally, the model is dynamically complete in the sense that it accounts for the dynamics of all the indicators used in the analysis. This leads the model to be a metric to measure the news associated with each realisation of the indicators used in the analysis, based on the effect that each realisation has on the expected economic growth. The empirical reliability of the model is evaluated by using in-sample data from January 2000 to December 2008. This exercise describes the main outputs that are obtained by the model in each of the automatised forecasts. The outputs show that the factor works reasonably well as an indicator of the recent economic evolution in Euro Area. As expected, the loading factors are positive and statistically significant which reinforces the standard view that the indicators are procyclical. In addition, as in Banbura and Runstler [11] or Camacho and Perez-Quiros [1], the empirical results show that a suitable treatment of publication lags may lead some indicators to provide important sources of information in predicting GDP beyond the information provided in the in-sample estimates of the loading factors.

The paper is organised as follows. Section 4.2 outlines the suggested methodology. Section 4.3 describes the empirical results of the model. Section 4.4 concludes and draws the lines for future extensions and improvements.

4.2 Description of the Model

In this section, we develop a model to compute short term forecasts of the Euro Area GDP growth in a real time environment from a set of indicators that may include mixing frequencies and missing observations.

4.2.1 Selection of indicators

The list of indicators which are included in the dynamic factor model can be classified into three main groups according to their frequency and potential delays in their publication. The first group contains one quarterly indicator; the so called second release of GDP, given that it is available for longer period compared to the flash and/or first release, although it exhibits significant delay in its announcement. The second group of indicators is formed by monthly hard indicators which are based on economic activity data. In particular, they are the Euro area Industrial Production Index (IPI, excluding construction), the Industrial New Orders index (INO, total manufacturing working on orders), the Euro area total retail sales volume, and the extra-Euro area Exports. Table 4.1 shows that these indicators exhibit large publication delays that range from 35 to 52 days. The last group of time series is constituted by soft indicators, which are based on survey data. The included soft indicators are the Euro-zone Economic Sentiment Indicator (ESI), the German business climate index (IFO), the Euro Area Consumer Confidence indicator (CCI) and the Belgium Overall Business Indicator (BNB). The main characteristic of all the soft indicators is that they are promptly available, as it can be observed in Table 4.1 since these indicators are available timely within the reference month and they start much earlier than the majority of the hard indicators.

To consider the full dynamic specification of all the variables included in the model, we deal with a relatively reduced number of indicators. However, it is not necessarily a disadvantage compared with large scale models. The problem of prior selection of variables is not fully solved in the generally proposed large scale models for the Euro area, because none of them uses all the information available in real time at all levels of disaggregation for all the countries and regions used in the analysis. Hence, prior to constructing the forecasts, the exercise of selecting the indicators used in the analysis have to be developed in any case. In addition, the level of complexity that large scale models incorporates in real time analysis is not always justified. In the context of forecasting, Bai and Ng [8] have recently suggested that the forecast accuracy does not necessarily increase with the number of series included in the model and Banbura and Runstler [11] find that most of the predictive content of their large scale model is contained in a small set of variables.

In this paper, the selection of indicators is based on the previous academic empirical literature but also on the choice of professional forecasters, meaning that the selection of indicators was made not only using the insights of previous academic studies of nowcasting, but also the practical insights provided by professional forecasters. After defining a set of core variables which is chosen by most of forecasters, we decided to include an additional variable when it increases the percentage of variance explained by the common factor. Depending on the nature of the data, these time series are transformed in different ways. GDP is used in quarterly growth rates. Hard indicators are transformed by taking monthly growth rates. However, soft indicators are included in levels. In addition, to be included in the dynamic factor model, all of these series have been normalised to have zero mean and unit variance. Missing data are conveniently replaced by random numbers which have been generated from $N(0,1)$. Retail sales, exports and industrial new orders start in the second half of the nineties and beginning of 2000 respectively. Second, hard indicators exhibit a publication delay of one or two months which leads to missing data at the end of the sample. Finally, the quarterly GDP growth does not contain monthly releases and, apart from the standard publication delays, they are available just the third month of each quarter.

4.2.2 Mixing Frequencies

The model is based on the idea of obtaining early estimates of quarterly GDP growth by exploiting the information in monthly indicators which are promptly available. Linking monthly data with quarterly observations needs to express quarterly growth rates observations as the evolution of monthly figures. Within this scope, let us assume that the levels of the quarterly GDP can be decomposed as the sum of three unobservable monthly values of GDP.

Let G_t be a quarterly series which is observable every third period and whose logs are integrated of order one. In this paper, series with this characteristic is the time series of GDP (second release). This series is the quarterly aggregates of monthly series, X_t, which are assumed to be observable in this section. Accordingly, we can construct quarterly time series from monthly series by adding the monthly values of the corresponding quarter.

$$G_t = 3(\frac{X_t + X_{t-1} + X_{t-2}}{3}) \tag{4.1}$$

which means that the quarterly levels are three times the arithmetic mean. However, handling with this definition would imply using non-linear state space models, which is rather troublesome. Mariano and Murasawa [83] show that if the sample mean of these three data can be well approximated by the geometric mean, the quarterly growth rate of GDP can be expressed as the average of monthly growth rates of latent observations. It is worth mentioning that if monthly changes are small enough the approximation error is almost negligible. In practice, monthly changes of production and employment are small (less than a percentage point) so the geometric approximation is suitable.

Hence, following Mariano and Murasawa [83], we assume that the flow data at any quarter is three times the geometric mean of the monthly issues within the given quarter:

$$G_t = 3(X_t X_{t-1} X_{t-2})^{1/3} \tag{4.2}$$

which yields,

$$lnG_t = ln3 + \frac{1}{3}(lnX_t + lnX_{t-1} + lnX_{t-2}) \tag{4.3}$$

Taking the three-period differences for all t and after some algebra, we can express the quarter-on-quarter growth rates (g_t) of the quarterly series as weighted averages of the monthly-on-monthly past growth rates (x_t) of the monthly series:

$$g_t = \frac{1}{3}x_t + \frac{2}{3}x_{t-1} + x_{t-2} + \frac{2}{3}x_{t-3} + \frac{1}{3}x_{t-4} \tag{4.4}$$

4.2.3 Bridging with factors

The practical application of the procedure described in the previous section exhibits two major econometric problems. The former is that the procedure is specified in monthly frequencies, although not all of our dataset is observed with the same frequency. This implies the need to estimate unobserved components such as monthly growth rates and quarterly growth rates for the first two months of each quarter. The latter is that the model has to handle with many missing observations since some series start too late, and some series, mainly those with longer publication delays, end too soon. Dynamic factor models are the appropriate framework to deal with the above mentioned drawbacks. These are also suitable models to characterise co movements in macroeconomic variables that admit factor decompositions. The single-index dynamic factor model is based on the premise that the dynamic of each series can be decomposed into two orthogonal components. The first component, called common component and denoted by f_t, captures the collinear dynamics affecting all the variables and can be interpreted as a coincident indicator of the GDP growth rate. The second component, called idiosyncratic component and denoted for each indicator j by u_{jt}, captures the effect of those dynamics which only affect that particular variable.

Let x_t be the monthly GDP growth rate and let z_t be the k-dimensional vector of economic indicators in monthly growth rates (hard indicators) or levels (soft indicators).[1] The model can then be stated as

$$\begin{bmatrix} x_t \\ z_t \end{bmatrix} = \beta f(t) + \begin{bmatrix} u_{yt} \\ u_{zt} \end{bmatrix} \tag{4.5}$$

[1] Indicators in levels create the problem of mixing integrated and stationary variables in the same specification. We solve the problem by considering, as pointed out in the works of the European Commission [54], that soft indicators are related with annual growth rates of the variable of interest, therefore, the level of the soft indicators depend on a 12 month moving average of the common factor, and this is the source of its unit root.

where $u_{zt} = (u_{1t}, u_{2t}, \ldots, u_{kt})$. The $(k+1)$ parameters in β are known as the factor loadings and capture the correlation between the unobserved common factor and the variables. To complete the statistical representation of the model, we assume the following dynamic specification for the variables.

$$\phi_y(L)u_{yt} = \epsilon_{yt} \tag{4.6}$$

$$\phi_f(L)u_{ft} = \epsilon_{ft} \tag{4.7}$$

$$\phi_i(L)u_{it} = \epsilon_{it} \tag{4.8}$$

where $\phi_y(L), \phi_f(L), \phi_i(L)$ are lag polynomials of order p, q and r, respectively.

In addition, we consider that all the errors in these equations are independent and identically normal distributed with zero mean and diagonal covariance matrix.

Dealing with balanced panels, i.e, when all the variables are observed in each period, the model can be easily stated in state space representation which can be estimated by maximum likelihood procedures, as it is shown by Hamilton [85]. In addition, the Kalman filter is the natural statistical method to deal with missing observations. Following Mariano and Murasawa [83] to handle with missing observations, we substitute the missing observations with random draws θ_t from $N(0, \sigma_\theta^2)$ which are independent of the model parameters. The substitutions allow the matrices to be conformable but they have no impact on the model estimation since the Kalman filter uses for them the data generating process of the normal distribution. In that sense, the missing observations add just a constant in the likelihood function of the Kalman filter process.

4.2.4 State Space Representation

The model can be written in state space form. Let us collect the quarterly growth rates of GDP and the annual growth rates of the indicators in the vector $Y_t = (y_t, z_t\prime)\prime$, and their idiosyncratic components in the vector $u_t = (u_{yt}, u_{zt}\prime)\prime$ So, the observation equation becomes:

$$Y_t = Hs_t + w_t \tag{4.9}$$

where $w_t \sim iN(0, R)$.

The transition equation is

$$s_t = Fs_{t-1} + v_t \tag{4.10}$$

where $v_t \sim iN(0, Q)$.

The remaining details about the specific form of the matrix H when dealing with quarterly growth rates and annual growth rates of monthly indicators and indicators in levels are described in the Appendix B.

One interesting result from dynamic factor models are the weights or cumulative impact of each indicator to the forecast GDP growth and can be obtained from the Kalman filter. Skipping details (that can be found on Appendix B), the state vector s_t can be expressed as the weighted sum of available observations in the past.[2] Assuming a large enough t such that the Kalman filter has approached its steady state, it holds that h-period ahead forecasts of GDP growth are approximately

$$y_{t+h} = \sum_{j=0}^{\infty} W_j' Y_{t-j} \tag{4.11}$$

In this expression, W_j is the vector of weights and leads the forecaster to compute the cumulative weight of series i in forecasting GDP growth as $\sum_{j=0}^{\infty} W_j(i)$, where $W_j(i)$ is the i-th element of W_j.

[2] See Stock and Watson [95] for further details of the exact derivation.

4.3 Empirical Analysis

Depending on the nature of the data, the time series are transformed in different ways. GDP is used in quarterly growth rates. Hard indicators are transformed by taking monthly growth rates. However, soft indicators are included in levels. In addition, to be included in the dynamic factor model, all of these series have been normalised to have zero mean and unit variance.

Following the method outlined above, missing data are conveniently replaced by random numbers which have been generated from $N(0, 1)$. First, many series start too late. Retail sales, industrial new orders and exports start rather later, mid nineties and beginning of 2000 respectively. Second, hard indicators exhibit a publication delay of one or two months which leads to missing data at the end of the sample. Finally, quarterly series do not contain monthly releases and, apart from the standard publication delays, they are available just the third month of each quarter.

The in-sample dataset which is available on January 2009 includes data from January 1991 to December 2008 and it is described in Table 4.1. The key series to be forecasted is quarterly growth rate of GDP which starts in February 1991 and ends in March 2007. Some of the eight indicators used in the model are shorter time series since they started to be published in the mid nineties. The four soft indicators, which are based on survey data, are plotted in Figure 4.3, whereas the evolution of hard indicators is plotted in annual growth rates. Despite the particularities exhibited in their evolution, all of them seem to share a common pattern with two significant slowdowns at the beginning and at the end of the sample. The particular publication pattern of these series can be examined in Table 4.1 which shows details of the sample period for every variable used in the estimation. Since GDP is published quarterly, the first two months of each quarter are treated as missing data. Typically, surveys have very short publishing lags since they are frequently published within the current month while hard data are released with a relatively longer delay of about two months. We put nine months of missing data after the last GDP growth observation because this is the horizon of our predictions. In January 2009, the last available release of GDP was in September 2008 and from this date until June 2009 the Kalman filter employed in the model will fill in these missing observations by computing dynamic forecasts for the last quarter of 2008 and the first two quarters of 2009. Accordingly, the nine-month forecasting horizon will be moved forward when GDP for the last quarter will be actually published.

The model estimated in this paper is based on the notion that co movements among the macroeconomic variables have a common element, the common factor, which moves according to the Euro Area business cycle dynamics. In this context, Figure 4.1 shows the estimated factor (bottom line) and the annual growth rates of the Eurocoin which is elaborated by the CEPR to account for the recent economic evolution in Euro Area. It is clear that the business cycle fluctuations of these two time series are in close agreement which validates the view that our factor agrees with the dynamics of the Euro Area economic activity. The indicator starts the nineties on its average value (dotted line) and suffers from the first temporary drop in 1992 and 1993. After the summer 1993, the indicator increased substantially and reached above-average values until mid nineties, when a milder drop characterised the winter 1995/96. Apart from a mild slowdown in 2001, during the next decade and until 2008 the indicator is uninterruptedly either on or above the average and its flatted trend marks the period of high growth which characterises the European economy in those years. At the beginning of 2008, there is marked breakpoint in the evolution of the factor. The figures of the indicator turned to negative and the pattern followed by the indicator became clearly negative trended. It is worth noting that, in terms of abruptness and deepness, the trend observed in all the economic indicators, but exports, are in line with the trend marked by the factor. Using the information up to January 2009, signals of recoveries are not expected by the model predictions at least until the end of 2009. To examine the correlation of the indicators and the factor, Table 4.2 shows the maximum likelihood estimates of the factor loadings and the standard errors within parentheses. Apart from GDP, the economic indicators with larger loading factors are those corresponding to Industrial New Orders, Industrial Production Index, Total Retail Sales and IFO index. The indicator with lower correlation with the latent common factor is exports which is only marginally significant. However, the estimates are always positive and statistically significant, indicating that these series are procyclical, i.e. positively correlated with the common factor. The fact that soft indicators do not have a high factor loading should not necessarily be interpreted as evidence in contrast to survey data. These are only in-sample estimates that can imply that ignoring the timely advantages of soft indicators would diminish their role in factor models when hard indicators are available.

Forecasts of GDP can be examined in Table 4.3. Figure 4.2 plots the monthly estimates of GDP quarterly growth rates along with their actual values. According to the methodology employed in this paper, the Kalman filter anchors monthly estimates to actual whenever GDP is observed. These forecasts, which are computed with information up to December 2008, anticipate that economic conditions are likely to increase in severity for the immediate future the negative path initiated in 2008. GDP is expected to grow at about 0.37 in the next month. It is worth mentioning that the projections of the related literature suggest a mild signal of starting recovery in February 2009. However, one should wait until updated data will be added to the model to consider whether this relatively mild signal will become a business cycle turning point. If the trend in the publication of bad news during the first months of 2009 continues, the model will suggest an economic deterioration for these periods. In addition to GDP forecasts, the model computes accurate forecasts for the whole set of indicators since their specifications are dynamically complete inside the model. The accuracy of these forecasts is crucial for forecasting exercises about the expected changes in GDP predictions against different possible next values of these indicators. Table 4.3 also shows the forecasts for the next unavailable month of each indicator. As recommended by Camacho and Perez - Quiros [21], imposing white noise idiosyncratic dynamics will produce very naive forecasts since it would restrict them to be proportional among the set of indicators, with constants of proportionality equal to the factor loadings.

One interesting result of dynamic factor models estimates are the weights or cumulative impact of each indicator to forecast GDP growth. The weights (standardised to sum 1) of the indicators in forecasting GDP growth are displayed in Table 4.4. According to the characteristic of the model, rows labeled as 2008.06 and 2008.09 reveal that, when GDP is published, the cumulative forecast weights of all the indicators on GDP forecasts are zero since the published data is a sufficient statistic for the actual figure and its cumulative forecast weight is one. The series only have weights different from zero during the periods in which the indicators are available but the corresponding GDP second is not. There is no data referring to periods after 2008.12 which implies that weights are zero after that date. Table 4.4 can also be used to show that ignoring the timely advantages of some indicators may lead to diminishing their role in factor analysis. Recall that IPI was the indicator with a higher factor loading. However, when some indicators are available but IPI is not, as in the case of the row labeled as 2008.12, the indicators that contribute in a higher scale to form GDP forecasts are the Total Retail Sales (weight of 0.35), and to a less extent the IFO indicator (weight of 0.18). When all the indicators become available (row 2008.10), Industrial New Orders (INO) have the largest cumulative weight (0.28) and Industrial Production Index (IPI) to a less extent in forecasting GDP growth.

4.4 Conclusions

Monitoring the Euro area business cycle developments has been, continues to be, and will be the source of many debates. However, the way to fill in missing observations in the time series, to deal with lack of timely information due to different publication dates and to choose appropriate Euro-wide aggregates remains an open question until now. This paper contributes to this literature by providing a method that handles with all of these problems but keeping the model sufficiently tractable to develop economic analyses in real time. Within this framework, we elaborate several empirical contributions.

We construct a new index of the Euro area economy that evolves according to the business cycle dynamics and exploits the information from hard and soft indicators. Moreover, we are able to show that the inclusion of these indicators contributes to the more accurate caption of business cycle dynamics.

The model developed in this paper provides a solid ground to account for two natural extensions. The former is related to the pre-seasonally adjustment of the series that is made by Eurostat. The usefulness of extending the baseline model to handle non-seasonally adjusted series, which would follow the lines suggested by Harvey and Shephard [67], is twofold. First, it would allow researchers to examine how different procedures handling seasonality may affect forecast performance in real time exercises. Second, it would constitute a unified model for forecasting macroeconomic series in those countries that produce non-seasonally adjusted aggregates.

The latter extension has to do with anticipating changes on business cycle regimes. Dynamic factors models are probably the most appropriate framework to combine the two key features of the business cycle: the idea of co movements among macroeconomic aggregates and the dichotomy between expansions and recessions. Following Diebold and Rudebusch [38], the extension would try to unify the linear dynamic factor model proposed in this paper and the non-linear Markov-switching methodology.

To sum up, the model presented in this paper can be used as a forecasting tool for Euro Area GDP growth, as it is automatically updated when new information becomes available, it constitutes a way of measuring the effects of news in the indicators on GDP growth rate, and it is a good benchmark to allow for extensions that could embrace in the same framework several problems such as seasonality and non-linearities that historically have been analysed separately from the forecasting exercise.

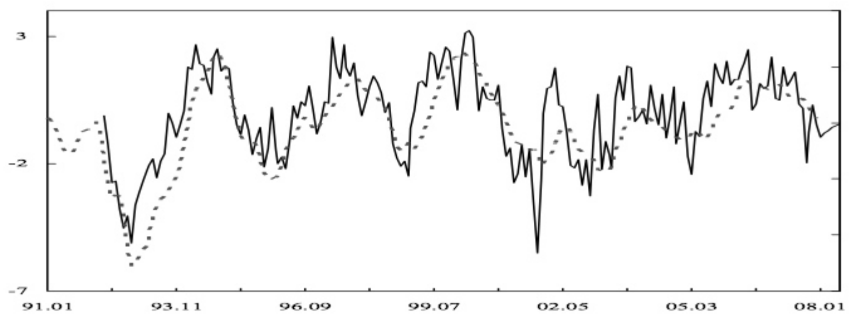


FIGURE 4.1: Line refers to the estimated factor with information available up to December 2008, dotted line is the Eurocoin indicator

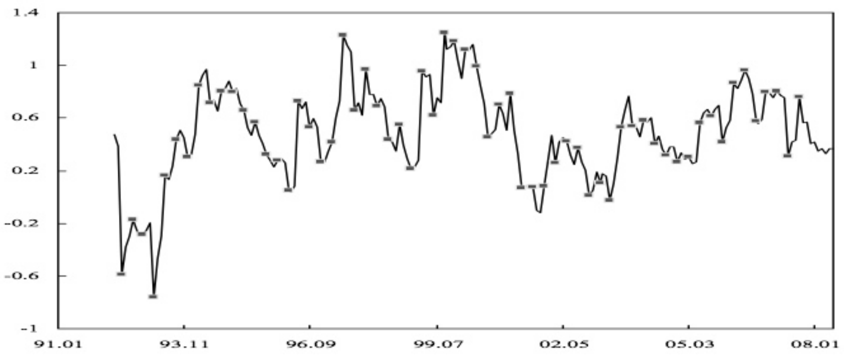


FIGURE 4.2: GDP growth rates are estimated from 1992.04 to 2008.06. Dots over the line refer to actual data

TABLE 4.1: Data Description

	Name	**Definition**	**Reporting Lag**	**Sample**
Quarterly Hard Indicators	GDP	Euro Area GDP Growth	102 days	02.91-03.07
Monthly Hard Indicators	IPI	Euro Area Industrial Production Index (excl construction)	42 days	01.91-12.08
	Sales	Euro Area Total Retail Sales Volume	35 days	01.00-12.08
	INO	Industrial New Orders Indices,Total manufacturing working on orders	52 days	01.95-12.08
	Exports	Extra- Euro Area Exports	45 days	01.00-12.08
Monthly Soft Indicators	ESI	Euro-Zone Economic Sentiment Indicator	0 days	01.91-12.08
	CCI	Euro Area Consumer Confidence Indicator	0 days	01.91-12.08
	IFO	Germany IFO Business Climate Index	-8 days	01.91-12.08
	BNB	Belgium Overall Business Indicator	5 days	01.91-12.08

Notes: (a) All hard indicators data (indicators of real activity) are growth rates of the seasonally adjusted series.
Soft Indicators (based on opinions surveys) are first differences of the seasonally adjusted series.
(b) Euro area refers to EMU-12 until December 2006 and EMU-13 afterwards.

Factor Loadings							
GDP	IPI	Sales	INO	Exports	ESI	IFO	CCI
0.11	0.19	0.06	0.16	0.10	0.05	0.06	0.05
(0.03)	(0.04)	(0.03)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)

Table 4.2: Standard errors are in parentheses. Data set ends in December 2008.

Model Based Forecasts							
GDP	IPI	Sales	INO	Exports	ESI	IFO	CCI
0.37	0.41	0.235	-1.123	0.526	98.182	103.415	28.6
(0.14)	(0.23)	(0.18)	(0.12)	(0.19)	(0.21)	(0.25)	(0.18)

Table 4.3: Standard errors are in parentheses. Data set ends in December 2008.

Cumulative weights

	GDP	IPI	Sales	INO	Exports	ESI	IFO	CCI	BNB
2008.06	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008.07	0.00	0.23	0.16	0.22	0.06	0.10	0.09	0.10	0.04
2008.08	0.00	0.23	0.13	0.26	0.08	0.05	0.07	0.13	0.05
2008.09	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008.10	0.00	0.23	0.18	0.28	0.06	0.03	0.05	0.09	0.08
2008.11	0.00	0.23	0.15	0.28	0.06	0.03	0.07	0.11	0.07
2008.12	0.00	0.00	0.35	0.00	0.00	0.12	0.18	0.20	0.15
2009.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 4.4: Standard errors are in parentheses. Dataset ends in December 2008.

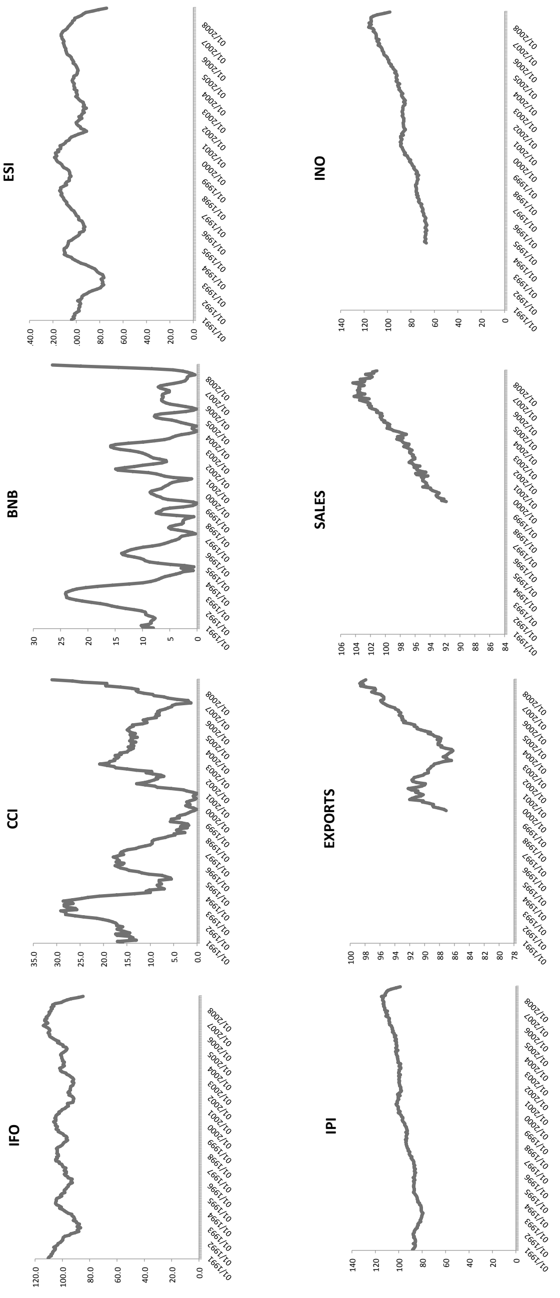


FIGURE 4.3: Evolution of Soft and Hard Monthly Indicators over the sample period

Annexes

Appendix A

Data Description and Transformation

The data set is comprised of 140 macroeconomic time series for the euro area spanning the period from January 2000 to December 2012 on monthly frequency. In order to deal with different data frequencies, we applied the method of cubic spline interpolation. By euro area, we mean the 16 countries that adopted the euro up to the beginning of 2009. For the purpose of analysing disruptions in the credit conditions in the euro area with data for the euro area as an entity (and not with data aggregated from the different member states) we had the choice of resorting to three different kinds of samples.

First, a fixed composition sample with the 11 countries that adopted the euro at the beginning of 1999, and therefore that have belonged to the euro area in all the period under analysis. Second, a fixed composition sample including the 16 countries that share a single monetary policy in 2009 (which means that the figures for the euro area in 1999 include for instance, the Slovakia data, although this country only adopted the euro at the beginning of 2009). Finally, a changing composition euro area,which means that the figures for the member countries are only considered as from the moment of their entrance. The third possibility was immediately discarded since we believe that the inclusion of the new countries could create a disturbance in the data at the moment of the entrance that could jeopardise our analysis. Between the two fixed composition panels, our first choice would be the 11 country panel, since those countries actually have shared a single monetary policy since 1999. However, a great fraction of the variables was not available for this panel. Therefore, the figures used in our work are those of a fixed composition 16 country euro area. Although the figures include five countries that did not share a single monetary policy in all the period under review, we believe that this will not impair the conclusions, given the rather low weight of these countries in the total of the euro area. (on average, in the period from 1999:1 to 2009:3, the weight of the five countries' GDP in the euro area GDP was around 3%; if we exclude Greece, which joined the euro area in 2001 the weight decreases.)

The series were taken from ECB Statistical Warehouse, Eurostat, Bank of England, Bank of Japan and Deutsche Bank for the Markit iBoxx Corporate Indices.

https://index.db.com/dbiqweb2/home.do?redirect=homepage

The format of the dataset Table 2.5 is as in all the papers of Stock & Watson:

series number; acronym; description and transformation code.The transformation codes are: 1 - no transformation; 2 - first difference; 4 - logarithm; 5 - first difference of logarithm; 0 - variable not used in the estimation (only used for transforming other variables). Acronym with * notation indicates a variable assumed to be "slow-moving" in the estimation of some specifications.

The estimation of the FAVAR model was based on the coding provided by Jean Boivin: http://neumann.hec.ca/pages/jean.boivin/research.html

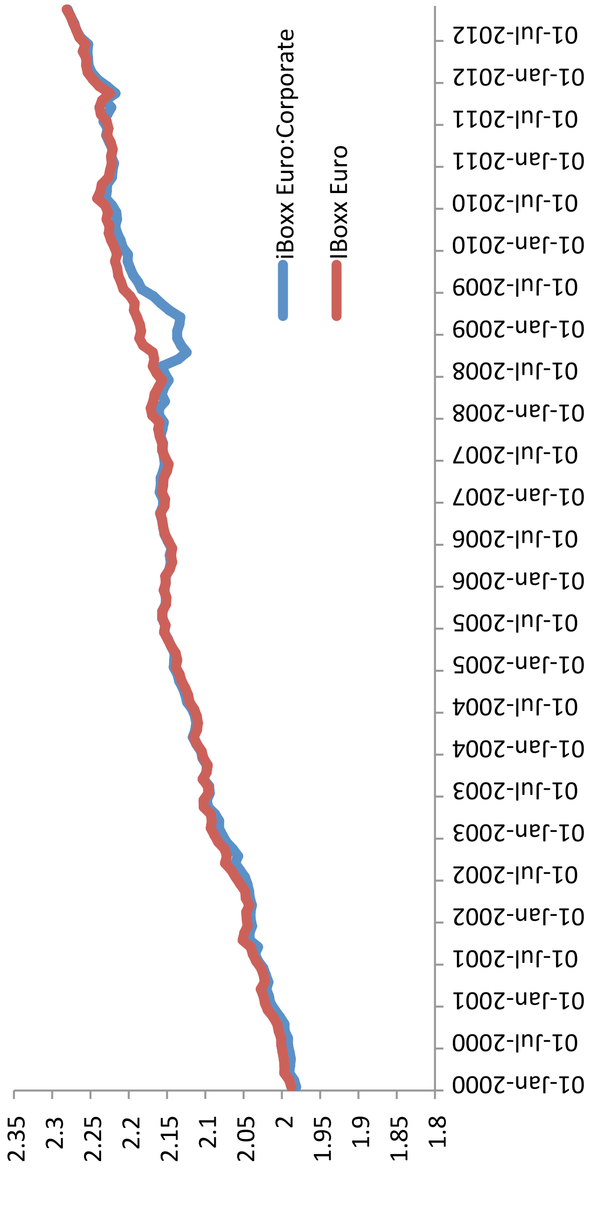


FIGURE A.1: iBoxxEuro Area Corporate and non-Corporate Data

Appendix B

State Space Representation

This appendix describes the state space representation of the dynamic factor model as described in Section 2. Let 0_{mI} and 1_{mI} be matrices of $m \times I$ zeros and ones,and I_m the m-dimensional identity matrix. Let us assume that $p = 2, q = 2, r = 2$ and that all variables are observed at monthly frequency. Finally since all indicators are treated in the same way, let us assume that we use just one indicator,hence $k = 1$. In this specific example, the observation equation $Y_t = Hs_t + w_t$ with $w_t \sim iN(0, R)$ becomes

$$Y_t = (y_t, z_t)\prime, \tag{B.1}$$

$$w_t = 0_{2,1} \tag{B.2}$$

$$R = 0_{2,2} \tag{B.3}$$

$$S_t = (f_T, \ldots, f_{t-11}, u_{yt}, \ldots, u_{yt-5}, u_{1t}, u_{1t-1}) \tag{B.4}$$

The matrix H becomes

$$\begin{pmatrix} H_{11} & 0_{1,7} & H_{12} & 0_{1,2} \\ H_{21} & H_{21} & 0_{1,6} & H_{22} \end{pmatrix}$$

,

where

$$H_{12} = \begin{pmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{2}{3} \end{pmatrix}, H_{11} = \beta_1 H_{12}, H_{21} = \beta_2 1_{1,6}, H_{22} = (1 \;\; 0)$$

Under the assumptions of the above mentioned example, the transition equation $s_t = Fs_{t-1} + v_t$ with $v_t \sim iN(0, Q)$ can be stated in the following way. Let Q be a diagonal matrix in which the entries of the main diagonal are determined by the vector:

The matrix F is:

$$F = \begin{pmatrix} F_1 & 0_{12,6} & 0_{12,2} \\ 0_{6,12} & F_2 & 0_{6,2} \\ 0_{2,12} & 0_{2,6} & F_3 \end{pmatrix},$$

where

$$F_1 = \begin{pmatrix} \phi_{f1} & \dots & \phi_{f6} & \dots & 0 & 0 \\ 0 & 1 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 1 & 0 \end{pmatrix}, F_2 = \begin{pmatrix} \phi_{y1} & \dots & \phi_{y5} & \phi_{y6} \\ 0 & \dots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 1 & 0 \end{pmatrix}, F_3 = \begin{pmatrix} \phi_{z1} & \phi_{z2} \\ 1 & 0 \end{pmatrix},$$

Appendix C

Indicators

1. EuroCoin: http://www.cepr.org/data/eurocoin/

2. DG-ECFIN: http://ec.europa.eu/economy_finance/indicators/euroareagdp_en.htm

3. EC-Macroeconomic Forecast: http://ec.europa.eu/economy_finance/about/activities/activities_keyindicatorsforecasts_en.htm

4. IFO INSEE ISAE: http://www.cesifo-group.de/portal/page/portal/ifoHome/a-winfo/d2kprog/30kprogeeo

5. OECD: http://www.oecd.org/department/0,3355,en_2649_34109_1_1_1_1_1,00.html

6. NBB: http://www.nbb.be/pub/stats/surveys/opinions.htm?l=en

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